A REVISED TECHNIQUE FOR MEASURING VERTICAL VELOCITY USING DROPSONDDES

by

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ABSTRACT

We did some research and wrote about the results. To be done when finished with all chapters...
This dissertation includes sections and chapters based upon research previously published in, or submitted as, peer-reviewed journal manuscripts by the author to adequately address the scientific concerns posed. Chapters 2 and 3 contain large excerpts, or rewordings, of the introductions, methods, data, results, figures, and some of the conclusions from Nelson et al. (2019a), Nelson and Harrison (2019), and Nelson et al. (2019b) (sections 2.2–3.1, 3.2, and 3.3, respectively). Nelson et al. (2019a) was published in *Monthly Weather Review*, and Nelson et al. (2019b) and Nelson and Harrison (2019) are in various stages of review or submission to the *Journal of Atmospheric and Oceanic Technology*. The results, appendix, and supplementary material from Nelson et al. (2019a) are also used as motivation for this dissertation and is referenced throughout this work. Permission to use these works as part of this dissertation is granted by the American Meteorological Society (AMS; Section 8a, https://www.ametsoc.org/ams/index.cfm/publications/ethical-guidelines-and-ams-policies/amscopyright-policy/) and is copyrighted by the AMS, 2019 (Appendix).

References:


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CHAPTER 1

Introduction

1.1 Motivation and purpose

In addition to the basic state variables (pressure, temperature, relative humidity, and horizontal wind) Global Positioning System (GPS) dropwindsondes (hereafter called “dropsondes”) can measure vertical velocity. Dropsonde-derived vertical velocities have been obtained since the mid 1960s (Bushnell et al., 1973) through a variety of techniques, but the present state of the art for dropsonde-derived vertical velocity error is approximately $\pm 1-2 \, \text{m s}^{-1}$ (Hock and Franklin, 1999; Stern et al., 2016; Nelson et al., 2019a). The vertical velocity errors need to be below $\pm 1 \, \text{m s}^{-1}$ to completely understand and defend the observations of convection and weaker vertical motions in many atmospheric phenomena such as tropical cyclones (TCs), thunderstorms, or boundary layer convection. In some circumstances, vertical velocity errors of $\pm 1-2 \, \text{m s}^{-1}$ could be the difference between diagnosing an updraft from a downdraft in the observed data (e.g., TC updrafts in Nelson et al., 2019a).

Accurate dropsonde-derived vertical velocities are also important to obtain information on atmospheric convection where Doppler radars do not perform well. Doppler radars have historically provided accurate measurements of vertical velocity within $1 \, \text{m s}^{-1}$, but they can only measure vertical velocity if there is enough precipitation or particles large enough to be detected by the radar (e.g., Atlas et al., 1973; Jorgensen et al., 1985; Black et al., 1996; Jorgensen et al., 1996; Matejka and Bartels, 1998; Heymsfield et al., 2010). Doppler radars are also beam averaging, meaning that vertical velocity, or energy, is averaged over
the beam volume and is not a true point measurement (Heymsfield et al., 2010; Ryzhkov, 2007). Dropsonde-derived vertical velocities fill this gap and complement radar data where there may not be precipitation or where point measurements are required. Dropsondes can also record vertical velocity profiles from their launched altitude to the surface in nearly all situations.

The need for more accurate dropsonde-derived vertical velocity measurements motivates this dissertation and serves as the basis for future dropsonde developments. This dissertation synthesizes 50 years of dropsonde-derived vertical velocity research and proposes to readdress the quality and accuracy of vertical velocity measurements by revisiting and revising older methods. Specifically, this work proposes to incorporate instrumentation on the eXpendable Digital Dropsondes (XDDs) manufactured by Yankee Environmental Systems to directly measure indicated vertical air speed (IAS) from a differential pressure sensor in a pitot-static system similar to what was originally done in the 1960s (e.g., Bushnell et al., 1973, Sections 2.1 and 2.5). The goal of this research is to reduce the dropsonde-derived vertical velocity error budget to $\pm 0.1 \text{ m s}^{-1}$. The corollary objectives of this dissertation are to: 1) provide a history of dropsondes and their developments (Sections 1.2, 1.3); 2) document previous methods to obtain dropsonde-derived vertical velocities (Chapter 2); 3) assess the strengths, weaknesses, and errors for the previous methods (Section 2.4, 2.5); 4) analyze the vertical velocities from previous studies using the XDDs (Chapter 3); 5) draw conclusions about performance requirements for XDDs and their launch spacing for future TC research missions (Section 3.3); 6) compare design characteristics for pitot-static measurements on the XDDs (Chapter 4); and 7) demonstrate the capabilities of dropsonde-derived vertical velocities using a pitot-static system (Chapters 5, 6).
1.2 Brief history of dropsondes

While the earliest balloon-borne observations of the atmosphere date back to the late 1800s and early 1900s (e.g., Rykatcheff, 1990), dropsonde technology is relatively young. Development of the National Center for Atmospheric Research (NCAR) dropsonde began in the early 1960s, with a principal goal of mapping the vertical velocity field of deep convective thunderstorms (Bushnell et al., 1973). This early NCAR dropsonde (hereafter referred to as “ED”) recorded atmospheric temperature ($T$), atmospheric pressure ($p$), dynamic pressure ($p_d$), and rate of change in pressure. The ED used a transponder method to calculate the dropsonde position by measuring the time delay of the pulse to estimate the distance from a set of two known fixed ground stations (Bushnell et al., 1973).

The initial NCAR ED design evolved into the Omega-based dropwindsonde (OD) in the early 1970s (Cole et al., 1973; Hock and Franklin, 1999; Wick et al., 2018). The OD operated at a very-low- frequency, used pulses of electromagnetic waves to obtain information on distance and location, and could be used in more remote locations than the ED (Cole et al., 1973; Govind, 1973). The OD also recorded data on $T$, $p$, and relative humidity ($RH$) (Govind, 1973). In 1987, the Office of Naval Research (ONR) conducted the Experiment on Rapid Intensification of Cyclones over the Atlantic using the NCAR developed Lightweight Long-Range (Loran) Digital Dropsonde (LDD; Hock and Franklin, 1999; Wick et al., 2018). The LDD was similar to the OD in that it also used phase shifts to obtain location information (Govind, 1973), but the LDD had improved horizontal wind measurements, was lighter than the OD, and had exchanged older analog circuitry for relatively modern digital circuitry (Hock and Franklin, 1999).

The modern NCAR GPS-based dropsonde began development in 1995 as part of the Airborne Vertical Atmospheric Profiling System (AVAPS; Hock and Franklin, 1999; Wang
et al., 2015). Wang et al. (2015) documented the major developments of AVAPS and the NCAR/Vaisala RD-93 dropsondes, RD-94 dropsondes, and mini-sondes (called NRD94 in Wick et al. (2018)). The mini-sonde is the most advanced research dropsonde available from NCAR at present, but future developments are expected regarding the $T$ and $RH$ sensors as well as the GPS chipset (Vömel et al., 2018). Specifications of the variables recorded, accuracy, and data acquisition frequency of the NRD94 are provided in Table 1.1 (Wick et al., 2018). AVAPS can currently support the telemetry of eight dropsondes in the air simultaneously (Wang et al., 2015; Black et al., 2017; Wick et al., 2018).

### 1.3 Introduction of the XDDs

The XDD is a light-weight, small dropsonde used with the High-Definition Sounding System (HDSS) manufactured by Yankee Environmental Systems (Fig. 1.1). A comparison of the size of the XDD to the RD-94 and mini-sonde is shown in Figure 1.2. Specifications of the variables recorded by the XDDs, accuracy, and data acquisition frequency are provided in Table 1.2 (Black et al., 2017; Nelson et al., 2019a). The XDD was developed off of the eXpendable Digital Radiosonde (XDR) used in the 2008 Arctic Mechanisms of Interaction between the Surface and Atmosphere (AMISA) project (Black et al., 2017).

The XDD has a twisted, slotted foam body and a cardboard outer shell with airflow cutaway windows (Fig. 1.1). This allows the XDD to spin during descent, obtain a ballistic trajectory, and promotes a stable fall mode. The XDD also features a quadrifilar antenna in the aft of the foam body and a loop nose antenna for transmitting and receiving data (Fig. 1.1).

At present, the HDSS consists of two, 48-dropsonde magazines, which allows a total of 96 dropsondes to be used in a single flight. With two dispensers, the launch rate can be
as quick as 5-s (Black et al., 2017). The HDSS can also uniquely identify and receive data from up to 40 dropsondes in the air simultaneously though the inclusion of forward error correction and time division multiplexing. The HDSS and the XDDs provide unprecedented temporal and spatial resolution of dropsondes from high altitudes (> 18 km).

Various test flights using the HDSS and XDD were conducted in from 2011–2014 including drops into Hurricane Gonzalo (2014) and has been shown to compare well to the NCAR/Vaisala RD-94 dropsonde. The XDDs have comparable wind and temperature measurements and resolution to the Vaisala RD-94 dropsonde (Black et al., 2017). Black et al. (2017) note that the largest discrepancies between collocated XDD and the RD-94 data are for RH. The RH sensors on the XDDs have a courser resolution and slower response rate, which leads to soundings being approximately 5% drier. Nonetheless, the XDDs allow for the collection of critical high-resolution observations of the thermodynamics, kinematics, and convection.

In 2015, the ONR conducted the Tropical Cyclone Intensity (TCI) experiment and launched an unprecedented 784 XDDs into four TCs: Erika (30 August), Marty (27–28 October), Joaquin (2–5 October), and Patricia (20–23 October) (Doyle et al., 2017). The XDDs were launched from a National Aeronautics and Space Administration (NASA) WB-57 aircraft at an altitude of approximately 19 km. The goal of TCI was to improve TC intensity prediction, especially in cases of rapid intensification (RI) and rapid weakening, and better understand TC structural change (Doyle et al., 2017). Specifically, TCI focused on the role of the outflow layer on intensity change in TCs.
Table 1.1: Variables recorded by the NRD94s and their range, resolution, repeatability, and data acquisition frequency. Adapted from Wick et al. (2018).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Range</th>
<th>Resolution</th>
<th>Repeatability</th>
<th>$\tau$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pressure</td>
<td>3–1080 hPa</td>
<td>0.1 hPa</td>
<td>0.4 hPa</td>
<td>2-Hz</td>
</tr>
<tr>
<td>Temperature</td>
<td>$-90^\circ$C$\text{ to } 60^\circ$C</td>
<td>0.2°C</td>
<td>0.2°C</td>
<td>2-Hz</td>
</tr>
<tr>
<td>Relative humidity</td>
<td>0–100%</td>
<td>1%</td>
<td>2%</td>
<td>2-Hz</td>
</tr>
<tr>
<td>Wind speed</td>
<td>——</td>
<td>0.1 m s$^{-1}$</td>
<td>0.2 m s$^{-1}$</td>
<td>4-Hz</td>
</tr>
<tr>
<td>Wind direction</td>
<td>0–360°</td>
<td>——</td>
<td>——</td>
<td>4-Hz</td>
</tr>
<tr>
<td>Fall speed</td>
<td>——</td>
<td>0.1 m s$^{-1}$</td>
<td>0.2 m s$^{-1}$</td>
<td>4-Hz</td>
</tr>
</tbody>
</table>

Table 1.2: Variables recorded by the XDDs and their range, resolution, accuracy, and data acquisition frequency. Adapted from Black et al. (2017).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Range</th>
<th>Resolution</th>
<th>Accuracy at 25°C</th>
<th>$\tau$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pressure</td>
<td>150–1150 hPa</td>
<td>2.5 hPa</td>
<td>1.5 hPa</td>
<td>2-Hz</td>
</tr>
<tr>
<td>Temperature</td>
<td>$-90^\circ$C$\text{ to } 60^\circ$C</td>
<td>0.016°C</td>
<td>0.14°C</td>
<td>2-Hz</td>
</tr>
<tr>
<td>Relative humidity</td>
<td>0–100%</td>
<td>0.1%</td>
<td>1.8%</td>
<td>2-Hz</td>
</tr>
<tr>
<td>Wind speed</td>
<td>——</td>
<td>0.1 m s$^{-1}$</td>
<td>0.2 m s$^{-1}$</td>
<td>4-Hz</td>
</tr>
<tr>
<td>Wind direction</td>
<td>0–360°</td>
<td>——</td>
<td>——</td>
<td>4-Hz</td>
</tr>
<tr>
<td>Fall speed</td>
<td>——</td>
<td>0.1 m s$^{-1}$</td>
<td>0.2 m s$^{-1}$</td>
<td>4-Hz</td>
</tr>
<tr>
<td>Sea surface temp.</td>
<td>0°C$\text{ to } 50^\circ$C</td>
<td>0.016°C</td>
<td>0.2°C</td>
<td>2-Hz</td>
</tr>
</tbody>
</table>

Figure 1.1: An example of an XDD manufactured in 2017.
Figure 1.2: Size comparison of an XDD, mini-sonde, and RD-94 dropsonde. Dropsondes approximately to scale.
CHAPTER 2

Previous dropsonde-derived velocity methods

There are three primary methods to obtain or calculate dropsonde-derived vertical velocities: 1) the pitot-static/differential pressure method (e.g., Bushnell et al., 1973); 2) the drag force method (e.g., Hock and Franklin, 1999); and 3) the estimated drag force method. The pitot-static method was introduced by P. Squires at NCAR and was used in the original ED in the 1960s and 1970s (Bushnell et al., 1973). The pitot-static method was ultimately abandoned in the later NCAR dropsonde iterations for unknown reasons (T. Hock and P. Black, personal communication), but it is hypothesized that it was abandoned after the passing of Squires in lieu of GPS-based or digital methods that did not require multiple large, analog transducers. NCAR has since used the drag force method for all dropsonde-derived vertical velocities. It is also possible to use a modified version of the drag force method in situations where the required information for the drag force method are not known a priori. The three methods are described in detail below and the typical errors, benefits, and limitations associated with each method are also discussed.

2.1 Pitot-static methods

The use of a pitot-static to obtain the velocity of air or the IAS of a moving object has been commonly used since the early 1700s with the invention of the pitot tube by Henri Pitot (Fig. 2.1; Pitot, 1732), eventually becoming the modern pitot-static design (Prandtl tube). The design was further improved upon in the 1850s by Henry Darcy (Darcy, 2017; Brown, 2003). The modern pitot-static system (Fig. 2.2) measures IAS by measuring the
differential pressure from the ambient air (static) and the dynamic pressure caused by motion (pitot). Pitot-statics are routinely used to obtain the horizontal airspeed of aircraft (e.g., Brousaides, 1983; Haering Jr., 1995; Federal Aviation Administration, 2016) or determine the flow velocity in a wind tunnel (e.g., Beck et al., 2010; Mitchell, 2013). The physics and methodology of a pitot-static is demonstrated by a simplified form of the Bernoulli principle as shown in Equations 2.1–2.3 (e.g., Brousaides, 1983; Federal Aviation Administration, 2016; Beck et al., 2010; Moum, 2015).

\[
\frac{d}{dz} \left[ \rho \frac{V^2}{2} + p + \rho gz \right] = 0 \tag{2.1}
\]

\[
\rho \frac{V^2}{2} + p + \rho gz = \text{constant} \tag{2.2}
\]

\[
V_2 = \sqrt{\frac{2(p_1 - p_2)}{\rho_2}} \approx V = \sqrt{\frac{2(dP)}{\rho}} \tag{2.3}
\]

In order for Equation 2.1 to be valid, then Equation 2.2 must identically be true. If variations in height \((z)\) are small, then the hydrostatic component of Equation 2.2 is negligible and an equality between \((p)\), \(\rho\), and velocity at some arbitrary point 1 and point 2 is established. The left side of Equation 2.3 solves for the velocity at point 2 and is simplified to the generic form on the right side of Equation 2.3. Therefore, IAS can be directly observed and calculated from the differential pressure if \(p_1\) is assumed to be the dynamic pressure and \(p_1\) is the static pressure.

The ED with a schematic of the pitot-static probe is shown in Figure 2.3. The pitot-static probe extended 5.5 inches below the dropsonde and had one pitot port (0.25 in diameter
tip) and six static ports (0.05 in diameter holes, 0.66 in from tip) large enough to ensure that blockage did not occur due to water (Bushnell et al., 1973). The tip has rounded edges and comes to a point at a 30° angle. The pitot-static tube was heated to 100°C to keep ice from building up on the probe (Bushnell et al., 1973).

Vertical velocity was obtained in two ways: 1) with a \( p_d \) transducer attached to the pitot port and a \( \frac{\partial p}{\partial t} \) transducer (also known as a p-dot transducer) attached to the static ports; and 2) with a \( p_d \) transducer attached to the pitot port and a standard pressure transducer attached to the static ports. The first method was filtered with a high-pass filter to remove low frequencies and the second method was filtered with a low-pass filter to remove high frequencies. The combination of both filtered signals yielded a final vertical velocity. The equations used to obtain the final vertical velocity are summarized below:

\[
\begin{align*}
    w_1 &= \sqrt{\frac{2p_d}{\rho} - \frac{1}{\rho g} \frac{dP}{dt}} \quad (2.4) \\
    w_2 &= \sqrt{\frac{2p_d}{\rho} - \frac{dz_p}{dt}} \quad (2.5) \\
    w &= HP(w_1) + LP(w_2) \quad (2.6)
\end{align*}
\]

\[
\rho = \frac{p}{R_d T_v}, \quad (2.7)
\]

where \( w_1 \) is the vertical velocity obtained with the pd and p-dot transducers, \( w_2 \) is the vertical velocity obtained with the \( p_d \) and pressure transducers, \( z_p \) is the hydrostatic height, \( t \) is time, \( \rho \) is density obtained by the ideal gas law using virtual temperature (Equation ...
2.2 Drag force methods

Since 1999, dropsonde-derived vertical velocities have been computed utilizing the dropsonde fall speed and the drag force equation assuming that the drag coefficient is independent of the Reynolds number (Hock and Franklin, 1999). The Reynolds number is the ratio of the relative airspeed and length scale to the viscosity of air (Equation 2.8):

\[ R_e = \frac{UL}{\nu}. \] (2.8)

Reynolds numbers below \(5 \times 10^5\) imply laminar flow plate object, and Reynolds numbers above \(5 \times 10^5\) imply turbulent flows (e.g., Happel and Brenner, 1965; Incropera et al., 2007). Dropsonde-derived vertical velocities are now routinely calculated in this manner (Wang et al., 2015). In more recent research, drag force dropsonde-derived vertical velocities have been used to examine the specifics of convection such as misovorticies and extremely strong updrafts in TCs (e.g., Aberson et al., 2006; Stern and Aberson, 2006; Stern et al., 2016).

The most common equation set used to calculate vertical velocity is as follows from Hock and Franklin (1999):

\[ V = \left( \frac{2mg}{C_dAp} \right)^{\frac{1}{2}} = \sqrt{\frac{m}{C_dA}} \sqrt{\frac{2g}{\rho}}, \] (2.9)

\[ w = V - V_f, \] (2.10)

where \(w\) is the vertical velocity, \(V\) is a theoretical terminal fall speed, and \(V_f\) is the true
fall speed of the dropsonde (note: $V$ and $V_f$ are positive pointing downward). On the right-hand side of Equation 2.9, the $\sqrt{\frac{m}{C_d A}}$ term is referred to as the ‘dropsonde parameter’ ($S_p$). In Equation 2.9, $g$ is the gravitational acceleration (positive term), $m$ is the mass of the dropsonde, $C_d$ is the drag coefficient, $A$ is the drag-affected area, and $\rho$ is density. The area used for the RD-94 dropsondes is the open area of the parachute and it is presumed to be representative for all dropsondes. The $C_d$ value used is typically 0.61 and the area is assumed to be fixed at 0.0676 m$^2$ or 0.09 m$^2$ (Wang et al., 2009; Stern et al., 2016).

Early studies like Hock and Franklin (1999) used the GPS fall speed for $V_f$, but more recent studies such as Wang et al. (2015) and Stern et al. (2016) used a hydrostatic differential pressure fall speed:

$$V_f = \frac{1}{\rho g} \frac{dP}{dt} \tag{2.11}$$

for $V_f$. A hydrostatic fall speed rather than the recorded GPS fall speed was used in these studies, because large, unrealistic and noisy GPS fall speeds occasionally occur (e.g., Fig. 2.4) and pressure is more accurate than GPS height (Stern et al., 2016). Figure 2.4 shows an example of erratic GPS fall speeds from an XDD sounding in Marty (2015) during TCI. The GPS fall speed above 15 km and between 6–8 km has high variance and do not match the hydrostatic fall speed (Fig. 2.4). The relatively weak GPS fall speeds aloft are not likely to be real, because they would indicate an unrealistically strong updraft of 15 m s$^{-1}$ far away from the core of the TC (318 km from the eye). This is also suspicious, because the GPS fall speed decreases nearly linearly with decreasing altitude until 14 km indicating a fall mode, stability, or GPS issue (Fig. 2.4). The large variance in the GPS fall speed, especially at high altitudes, is likely due to changing GPS constellations (Berg, 2003, Lee Harrison,
personal communication). Large variances in the lowest few kilometers above the surface are occasionally observed in both the XDD data (Fig. 2.4) and RD-94/NRD94 data (Vömel et al., 2018). If GPS fall speeds are used to derive vertical velocity, the fall speeds should be heavily screened based upon the indicated differential pressure fall speed or heavily filtered.

2.3 Estimated drag force methods

There are three variants of the estimated drag force method to use when the exact values for $C_d$ and $m$, or the variance in those values, are unknown. These methods are proposed because the exact drag coefficient of the XDDs used in TCI was not known a priori and the variances in the mass and area of the XDDs used were not known. If it is assumed that the dropsonde parameter for any given dropsonde is constant as it falls from some arbitrary altitude ($Z$) to the surface ($Z_o$), then Equation 2.12 must be true:

$$V(Z) = V(Z_o) \sqrt{\frac{\rho(Z_o)}{\rho(Z)}}$$

(2.12)

The $V(Z_o)$ and $\rho(Z_o)$ terms represent the estimated surface fall speed and density of a dropsonde. The three methods to obtain $V(Z_o)$ and $\rho(Z_o)$ include: 1) an individualized last data point fall speed and density (M1), 2) a mean or median last data point fall speed and density from dropsondes launched outside of convection (M2), and 3) an estimated $V(Z_o)$ from a mean (or median) $S_p$ from dropsondes outside of convection and the last data point density from dropsondes inside of convection (M3). It is assumed that dropsondes were launched outside of convection if the sounding profiles were unsaturated and infrared (IR) cloud top temperatures were above $-30^\circ$C. The $-30^\circ$C threshold was chosen, because it matches the warmest IR brightness temperatures for all deep convection observed by Jiang.
and Tao (2014).

The benefit to using an individualized fall speed (M1) is that it is self-calibrating and accounts for mass differences from dropsonde-to-dropsonde including manufacturing differences and any icing or riming that does not melt off of dropsondes launched into deep convection. The last data point fall speed, however, may not represent the still-air fall speed for the individual dropsonde, because low-level updrafts or downdrafts could still be present or the dropsonde could be in a non-stable fall mode. This is still a problem even if a threshold is used for the height of the last data point (Fig. 2.5). The use of a mean or median last data point outside of convection (M2) is a non-self-calibrating estimation of $V(Z_o)$ and $\rho(Z_o)$ but is less prone to errors due to low-level updrafts or downdrafts affecting the value of $V(Z_o)$ in convective areas. The third method is a hybrid of the first two methods. Figure 2.6 shows that the variance in the estimated $V(Z_o)$ from $\rho(Z_o)$ in convection and the median $S_p$ from data outside of convection is considerably smaller than the observed $V(Z_o)$ for the same dropsondes during TCI. The difference in the variance was 1.74 m$^2$ s$^{-2}$. The median $S_p$ was 4.22 kg$^\frac{1}{2}$ m$^\frac{3}{2}$ (Fig. 2.6). The reduced variance using M3 compared to the others is a consequence of the high confidence in the measurements of pressure, and subsequently density, for dropsondes. The standard deviation of the last data point density was small at 0.02 kg m$^{-3}$ (Fig. 2.6).

A comparison of the vertical velocities from TCI computed with the three methods using notched boxplots is provided in Figure 2.7. Also included in Figure 2.7 is M3 using the GPS fall speed for $V_f$ rather than a hydrostatic fall speed (M3b). None of the notches of the box plots overlap, which indicates that the medians of all the methods are statistically different, but the differences are small enough to not be physically significant. M1 has the largest variance, with a standard deviation of 2.26 m s$^{-1}$. The increased variance is not likely
physical, because it occurs by using different values of $\rho(Z_0)$ and $V(Z_0)$ and an individualized dropsonde parameter. M2 and M3 have the lowest variance in vertical velocity from TCI, which suggests that M2 and M3 are more robust than M1. It should also be noted that variance of the vertical velocity is increased in the TCI dataset if the GPS fall speed was used (Fig. 2.7).

2.4 Benefits and limitations

Regardless of the method used to obtain the vertical velocity, significant errors may still exist. In this section, the benefits and limitations of the previously discussed dropsonde-derived vertical velocity methods are detailed in depth. The typical errors associated with each of the three methods are also discussed.

One benefit of a pitot-static system on a dropsonde is that the IAS obtained is a direct, physical measure of the dropsonde fall speed. The vertical velocity calculations for the pitot-static outlined by Bushnell et al. (1973) are also independent of the mass, drag coefficient, and area, which are major sources of error in the drag force methods. The drag force methods either use integrated hydrostatic fall speeds over fairly large distances (e.g., Stern et al., 2016) or GPS fall speeds that are prone to large amplitude noise (Fig. 2.4). The ED dropsonde directly recorded the hydrostatic fall speed with a p-dot transducer (Bushnell et al., 1973). Bushnell et al. (1973) also note that the ED had a Reynolds number of approximately $5 \times 10^5$, where transition from laminar to turbulent flow occurs.

Bushnell et al. (1973) state that EDs falling at this ‘critical’ Reynolds number can lead to situations where the drag coefficient can change rapidly and irregularly. However, it is not clear if the drag coefficient fluctuations were due to parachute or drag device deformations. Regardless, it is plausible that the drag coefficient can vary for a dropsonde parachute as
it falls, which causes vertical velocity errors when using the drag coefficient methods in convection.

High accuracy of IAS from a pitot-static on current operational aircraft is crucial for safe flights to be conducted (Haering Jr., 1995; Federal Aviation Administration, 2016; Carlson, 2012), so errors in IAS from any pitot-static need to be small. The accuracy of many pitot-static IAS probes is between 0.5–2 m s$^{-1}$ and are functions of small errors in the differential pressure (Bushnell, 1966; Bushnell et al., 1973; Brousaides, 1983; Pearson, 1983; SpaceAge Control, 1998; Barfield, 2013). The five primary sources for error are: 1) port blockage (Federal Aviation Administration, 2016); 2) port placement error (Haering Jr., 1995; Carlson, 2012); 3) angle of attack (Pearson, 1983; Haering Jr., 1995; Beck et al., 2010); 4) normal instrumentation error (Carlson, 2012); and 5) low speed errors (SpaceAge Control, 1998). Over the past 160 years, many studies have been conducted to improve the design of the pitot-static system to decrease errors and offer more consistent calibration (e.g., Salter et al., 1965; SpaceAge Control, 1998; Federal Aviation Administration, 2016; Beck et al., 2010; Carlson, 2012; Reuder et al., 2013; Abdelrahman et al., 2015).

Port blockage becomes a problem when water, ice, or other debris block the port holes and prohibit the pitot-static from working effectively (Federal Aviation Administration, 2016). If the pitot tube is blocked and a leak port is present, then the air inside the tube will eventually leak out and the pressure with match the static pressure, giving a zero-differential pressure. If the pitot tube is blocked and no leak port is present, or the leak port is blocked, then the differential pressure will decrease with decreasing height to reflect the change in height. If the static port becomes blocked and the pitot port is clear, the differential pressure will be biased to positive values as the object descends. If the pitot and static ports are both blocked, the differential pressure will be zero.
Port placement errors, also known as position errors, occur as a result of the location of the pitot and static ports relative to the object body (Haering Jr., 1995; Carlson, 2012). Position errors primarily occur because any object within a stream of air disrupts the flow and can cause local pressure perturbations that affect the pitot-static measurement (Bushnell et al., 1973; Haering Jr., 1995). Compressibility and shock waves related to the disruption in the flow by the object can also affect the measurement, but this is primarily at speeds greater than approximately 100 m s\(^{-1}\) or a Mach number of 0.3 (Haering Jr., 1995). Such high fall speeds are not observed with any current dropsonde. Position errors are also a function of the angle of attack.

The angle of attack of the pitot-static probe could have a significant effect on the indicated velocity (Pearson, 1983; Haering Jr., 1995; Beck et al., 2010; Carlson, 2012). The design, shape, and angle of the probe tip dictate the severity of the angle of attack error and the angles of attack that are suitable for the specific probe (Haering Jr., 1995). Beck et al. (2010) documented the change in the pitot-static measurements for a specific probe as a function of angle of incidence through wind tunnel tests (Fig. 2.8). The pressure coefficient (\(C_p\)), which is the ratio of the calibrated pitot-static indicated pressure to the true wind tunnel differential pressure, reaches a minimum when the pitot-static probe is perpendicular to the incoming flow (Fig. 2.8). The maximum errors in this extreme situation were 7–8 m s\(^{-1}\) at wind tunnel speeds of 35–42 m s\(^{-1}\). Given that modern dropsondes either fall with a parachute (e.g., RD-94s) or with a ballistic trajectory (e.g., XDDs), such extreme angles of incidence and large errors are not likely. At 35 m s\(^{-1}\), \(C_p\) values of 0.95 or 1.05 correspond to errors of approximately 1 m s\(^{-1}\) (Fig. 2.8).

There are also inherent, normal, instrumentation errors associated with the differential pressure sensor upon leaving manufacturing. Instrumentation companies can calibrate the
sensors before leaving and provide documentation on the expected error range of the sensor (e.g., All Sensors, 2019), but the errors still affect the confidence in the measurement. Bushnell et al. (1973) note that the typical instrumentation errors with the dynamic pressure and static pressure transducers ranged from $1 \times 10^{-4}$–0.8-hPa on the EDs.

At low air velocities, the ratio of the indicated air speed to the total error range decreases and tends toward unity (SpaceAge Control, 1998). At these low ratios, the total errors begin to saturate the signal and the percent errors become significant. This is an inherent problem for measuring any meteorological variable that can decrease to zero or below a detectable limit. SpaceAge Control (1998) note that at 12 m s$^{-1}$, the velocity errors for their wind tunnel pitot-statics were $\pm 2.5\%$ (0.3 m s$^{-1}$). At higher velocities, error dropped below $\pm 0.7\%$.

The dropsonde-derived vertical velocities using the pitot-static method on the ED were compared to sailplane vertical velocity observations in quiescent conditions on two different days in northeastern Colorado (Bushnell et al., 1973). Figures 2.9 and 2.10 show the dropsonde-derived vertical velocities and the sailplane vertical velocities from 21 and 25 April 1972. The average true vertical velocity in each profile is assumed to be zero, but the average sailplane vertical velocity was $-0.2$ m s$^{-1}$ and $0$ m s$^{-1}$, respectively. The typical vertical velocity error bounds associated with this methodology were estimated by the difference between the average pitot-static indicated fall speed and geometric fall speed ($\Delta w$). The differences were on the order of $\pm 1$ m s$^{-1}$ and the standard error of the dropsonde-derived vertical velocities and the sailplane vertical velocities was $0.6$ m s$^{-1}$ (Bushnell et al., 1973).

Recent advancements in unmanned aerial vehicles (UAVs) have allowed for meteorological wind measurements using more modern pitot-static probes (Reuder et al., 2009, 2013;
Niedzielski and Coauthors, 2017). Reuder et al. (2009) found that pitot-static UAV-derived horizontal wind speeds and Vaisala RS92 radiosonde data agreed within 0–2 m s$^{-1}$, with the largest discrepancies due to sampling differences and not systematic errors in the measurement or methods. Niedzielski and Coauthors (2017) also found that the differences between UAV-derived horizontal wind speeds and nearby tower data were at least 1–2 m s$^{-1}$. Vertical velocity UAV measurements taken at 100-Hz had low standard deviations of 0.31 m s$^{-1}$ (Reuder et al., 2013).

Dropsonde-derived vertical velocities using drag force methods are attractive, because no additional specialized instrumentation is needed beyond what is currently on modern dropsondes, the calculations are straightforward and based upon Newtonian physics, the errors are easily characterized and estimated, and they have been the common-place, standard dropsonde-derived methods for almost 20 years. The potential errors associated with drag force-based calculations like Hock and Franklin (1999), Wang et al. (2015), and Stern et al. (2016): 1) added (subtracted) mass from icing (de-icing); 2) variations in the dropsonde drag area; 3) variations in drag coefficient; and 4) presence of low-level updrafts or downdrafts. The first three affect the calculation of $S_p$. While mass changes and dropsonde-to-dropsonde mass differences are more easily understood, variations in $C_d$ and $A$ are not. Li and Miller (2014a,b) assume that the drag coefficient and drag affected area of a dropsonde is constant, regardless of the angle of incidence. One can adjust the variables and parameters in Equations 2.9 and 2.10 to estimate the sensitivity or potential errors in dropsonde-derived vertical velocity using the drag force methods.

The potential errors/sensitivity associated with the vertical velocity measurements using the Hock and Franklin (1999) methodology with RD-93 and RD-94 dropsondes and a hydrostatically derived $V_f$ is outlined in the appendix of Stern et al. (2016). The sensitivities
are shown in Figure 2.11, which was adapted from Stern et al. (2016). The true mass of
the dropsonde used in the example sounding was 389 g, drag coefficient was assumed to be
0.61, and the area was assumed to be 0.09 m$^2$ (dashed blue lines in Fig. 2.11). Peak vertical
velocity varied by 2–5 m s$^{-1}$ by changing the variables within the ranges examined by Stern
et al. (2016). The authors state, however, that overall bias at low levels associated with
uncertainty in mass (60–80 g difference), area, and drag coefficient is less than 1 m s$^{-1}$.

A similar analysis was conducted for the XDDs using the M3 estimated drag force
method discussed previously. For the purposes of discussion, it is assumed that the mass of
the XDD is 0.058 kg, the diameter is 0.066 m (Black et al., 2017), and the drag coefficient
is 0.95. A drag coefficient of 0.95 was obtained by solving for $C_d$ given the median $S_p$ from
dropsondes launched outside of convection and the mass and area. For the four primary
sources of error described previously, errors are largest aloft (Fig. 2.12). This is due to a
larger ratio of $\rho(Z_o)$ to $\rho(Z)$ in Equation 2.12. A $\pm 1$ g change in mass (based upon weight
measurements of eight XDDs) leads to errors of approximately $\pm 1$ m s$^{-1}$ aloft (Fig. 2.12a). If
the diameter of the dropsonde varies by 0.0002 m (based upon caliper measurements of three
XDDs), errors in vertical velocity of 0.14 m s$^{-1}$ are possible aloft (Fig. 2.12b). Variance in
the drag coefficient of 0.1 leads to errors of $\pm 2$ m s$^{-1}$ aloft (Fig. 2.12c). Lastly, the presence
of low-level updrafts and downdrafts affecting the median by $\pm 0.5$ m s$^{-1}$ (close to standard
deviation of the sea-level fall speed of 90 XDDs; Fig 2.6 b) leads to errors of $\pm 1.36$ m s$^{-1}$
aloft (Fig. 2.12d).

The total standard deviation of the errors can be calculated by:

$$\sigma_T = \sqrt{\sigma_m^2 + \sigma_A^2 + \sigma_{C_d}^2 + \sigma_{w_L}^2}$$ \hspace{1cm} (2.13)
The total standard deviation of the errors using the M3 methodology is approximately 0.86 m s\(^{-1}\) in the low-levels and 2.39 m s\(^{-1}\) in the upper-levels. This agrees well with the findings of Stern et al. (2016). A 1 g variation in the RD-94 calculation of vertical velocity leads to an error of approximately ±0.25 m s\(^{-1}\) at 12 km, which is similar to the XDDs at 12 km (Figs. 2.11 and 2.12). The RD-94s and XDDs also have comparable errors in vertical velocity due to ±0.05 variations in \(C_d\) (Figs. 2.11 and 2.12). Stern et al. (2016) allow the RD-94 drag area to vary in size more what was done for the XDDs, but only small deviations in the XDDs are expected due to manufacturing differences and ice build-up (Fig. 2.12c). The area used with the RD-94 calculations is the area of the primary parachute, which can deform and change size during descent. Large deformations and pendulum motions of the RD-94s require extensive filtering of vertical velocity. Therefore, errors associated with area are expected to be smaller in the XDDs than the RD-94s using these drag coefficient-based methodologies.

An additional source of error, GPS fall speed error, only matters if the GPS fall speed is used for \(V_f\). The u-blox 6 GPS chip used on the XDDs during TCI is claimed to have a velocity accuracy of 0.1 m s\(^{-1}\) at a circular error probability of 50\% (U-blox, 2019). However, GPS constellation errors, such as dropsondes switching to different GPS constellations, can cause large, unphysical outliers in the GPS fall speed and dropsonde-derived vertical velocity (e.g., Fig. 2.4). At the surface, the variances in GPS fall speed are small but not negligible (Fig. 2.6b). Figure 2.6b shows that the standard deviation of the last data point fall speed for dropsondes launched outside of convection during TCI was approximately 0.9 m s\(^{-1}\). This agrees well with the standard deviation of the near-surface fall speed of XDDs launched in test flights in Black et al. (2017). While the variance and standard deviation of the last data point GPS fall speeds include errors and variances with atmospheric variances in each
sounding such as the presence of weak low-level updrafts or downdrafts and variations in dropsonde drag, it is the best estimation of the GPS fall speed variances and errors in the XDDs used during TCI.

Regardless of the dropsonde used, the typical errors for the two drag force methods range from $\pm 1–2 \text{ m s}^{-1}$, which means that drag force-based methods do not work well for, and are not accurate for, weak vertical velocities. This is a major problem for atmospheric studies of weak convection such as orographic forcing (e.g., Wang et al., 2009) or analysis of vertical velocities in TCs (e.g., Black et al., 1996). However, these methods are sufficient in studies focusing on extremely strong convection, where the errors fall below 10% of the desired signal (e.g., Stern et al., 2016). In such situations, the estimated drag force methods are useful in that no knowledge of the drag coefficient, nor the mass, is required. The only required information for the M3 estimated drag force method is an accurate measure of surface fall speed outside of convection and profiles of pressure and temperature to altitudes relatively near the surface.

### 2.5 Proposal and hypothesis

The Reynolds number for the XDDs can be approximated by Equation 2.8 assuming the length scale is the length of the dropsonde (7 in.; Black et al., 2017). This was done for 90 XDDs launched into clear air during TCI (Fig. 2.13). The Reynolds number is a function of fall speed, and thus a function of altitude, but maximizes at approximately $2.8 \times 10^4$ (Fig. 2.13). This implies laminar flow for the XDDs (Happel and Brenner, 1965; Incropera et al., 2007). Because of the laminar flow and lack of a parachute, the drag coefficient is not expected to radically change during descent. This does not imply, however, that the drag coefficient is uniform from dropsonde-to-dropsonde or that the drag coefficient is independent
of icing. This means that drag coefficient methods to calculate vertical for the XDDs are still problematic given the errors described previously.

Given the significant technological and mechanical advancements in the past 50 years since the introduction of the pitot-static IAS in dropsondes, the capabilities and accuracy of a dropsonde-derived vertical velocity through a pitot-static IAS should also, hypothetically, improve. It is proposed here to revisit and revise the older pitot-static dropsonde-derived vertical velocity methods by Bushnell et al. (1973) on the XDDs. In this dissertation, an attempt is made to decrease the error in vertical velocity measurements on the XDDs from $\pm 1\text{–}2 \text{ m s}^{-1}$ using the M3 estimated drag coefficient method to an average of $\pm 0.1 \text{ m s}^{-1}$ by using modern pitot-static methods in quiescent conditions. By directly measuring the IAS and using an integrated hydrostatic fall speed, GPS location and fall speed errors, such as in Figure 2.4, will not impact vertical velocity calculations. Further, the vertical velocity calculations will be independent from errors associated with variances in the mass, drag coefficient, area, and low-level updrafts or downdrafts with the previous drag force methods.

Three variations of the classic pitot-static design were considered and tested: 1) modified pitot-static (Fig. 2.14a, b); 2) venturi-static (Fig. 2.15a, b); and 3) pitot-venturi (Fig. 2.16a, b). The three designs are set-up to measure the differential pressure in three different ways across the XDDs as they fall. The modified pitot-static is similar to the traditional pitot-static in that it measures the dynamic pressure through the leading-edge port near the center of the nose, but the static is measured from the side of the dropsonde and is shielded from the ram air pressure caused by descent and updrafts or downdrafts (Fig. 2.14a, b). If the dropsonde is assumed to be a blunt cylinder with a length to diameter ratio of approximately three (Black et al., 2017), a fairly expansive wake is expected to form for flows with $R_e \approx 1\text{e}10^4$ (Fig. 2.17; Higuchi et al., 2006). In this situation, a low pressure is expected
to form within the wake. A venturi-static would measure the difference between the static pressure at the side of the dropsonde and the low-dynamic pressure in the aft of the dropsonde either near the center through the antenna or to one side of the antenna behind the foam body (Fig. 2.15a, b). The pitot-venturi measures the difference between the dynamic pressure at the leading-edge of the dropsonde as it descends and the low-dynamic pressure at the aft of the dropsonde either near the center through the antenna or to one side of the antenna behind the foam body (Fig. 2.16a, b). The benefits and limitations of each design are summarized in Table 2.1. The optimum differential pressure measurement, however, would be from a venturi-static system (Fig. 2.15 a, b) as it would be the least likely to be affected by icing.

Because the typical fall speeds of the XDD range from 0–50 m s$^{-1}$, with an estimated sea-level fall speed of 18 m s$^{-1}$, small biases and errors are critical. A 1-2% error like those described by SpaceAge Control (1998) would lead to vertical velocity errors of 0.2–0.4 m s$^{-1}$ at the surface and 0.5–1 m s$^{-1}$ at 17.5 km for the XDDs. If specialized a small-range, low-differential pressure (low-dP) sensor like the DLHR-L05D-E1BD was used, then relatively large errors associated with low airspeeds decrease (Fig. 2.18). The DLHR-L05D-E1BD sensor is an I2C/Serial Peripheral Interface with digital output (bits) and an overall accuracy of 0.25% (All Sensors, 2019). This would correspond to vertical velocity accuracies of 0.05 m s$^{-1}$ at the surface and 0.1 m s$^{-1}$ aloft. The sensor is rated for temperatures of $-20^\circ$C to $85^\circ$C (All Sensors, 2019). A table of the specifications for the sensor is provided in Table 2.2. It is expected that differential pressure measurements using the modern DLHR-L05D-E1BD sensor will provide lower clear air dropsonde-derived vertical velocity errors than the Bushnell et al. (1973) study.

The proposed error budget goal is partitioned into two components: 1) $\pm 0.05$ m s$^{-1}$
instrumentation error, and 2) $\pm 0.05 \, \text{m s}^{-1}$ tube/port placement error. The first component comprises of the overall accuracy of the sensor, temperature dependent biases, instrument precision, and input voltage errors. The second component is the error associated with the sensitivity of the differential pressure measurement to the exact placement of the ports and tubes on the XDDs. The error budget of 0.1 m s$^{-1}$ matches the velocity accuracy in the data sheet for the u-blox 6 GPS chip (U-blox, 2019). The proposed error budget does not take into account errors associated with port blockage or icing.

Table 2.1: Benefits and limitations of the differential pressure (dP) methods analyzed.

<table>
<thead>
<tr>
<th>dP method</th>
<th>Benefits</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pitot-static</td>
<td>1) Likely reproducible from drop-to-drop</td>
<td>1) Vulnerable to icing errors;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2) Pitot port blockage;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3) Static needs to bypass circuit board and penetrate side sleeve</td>
</tr>
<tr>
<td>Static-venturi</td>
<td>1) Least prone to icing errors</td>
<td>1) Venturi port may be hard to reproduce from drop-to-drop;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2) Venturi port placement harder;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3) Static needs to bypass circuit board and penetrate side sleeve</td>
</tr>
<tr>
<td>Pitot-venturi</td>
<td>1) No side port placement issues;</td>
<td>1) Vulnerable to icing errors;</td>
</tr>
<tr>
<td></td>
<td>2) No competing issues with dropsonde rotation/angle of</td>
<td>2) Venturi port may be hard to reproduce from drop-to-drop;</td>
</tr>
<tr>
<td></td>
<td>attack;</td>
<td>3) Pitot port blockage;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4) Venturi port placement harder</td>
</tr>
</tbody>
</table>

Table 2.2: Sensor specifications for the DLHR-L05D-E1BD, adapted from All Sensors (2019). Full scale span is abbreviated as FSS.

<table>
<thead>
<tr>
<th>Specification</th>
<th>Value (typical)</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operating range</td>
<td>$\pm 12.44$ hPa</td>
<td>497.7 hPa</td>
</tr>
<tr>
<td>Proof pressure</td>
<td>497.7 hPa</td>
<td>689.5 hPa</td>
</tr>
<tr>
<td>Burst pressure</td>
<td>746.5 hPa</td>
<td>746.5 hPa</td>
</tr>
<tr>
<td>Nominal span</td>
<td>$\pm 0.4 \times 2^4$ counts</td>
<td>689.5 hPa</td>
</tr>
<tr>
<td>Common mode pressure</td>
<td></td>
<td>689.5 hPa</td>
</tr>
<tr>
<td>Resolution</td>
<td>16 bit</td>
<td>16 bit</td>
</tr>
<tr>
<td>Total Error Band</td>
<td>0.5% FSS</td>
<td>1.0% FSS</td>
</tr>
</tbody>
</table>

25
Figure 2.1: Henry Pitot's original pitot tube design. The two tubes (labeled A and B) were lowered into the flow and the pressure was recorded as the difference in the water level between the two tubes (Brown, 2003). This figure is adapted from Brown (2003).
Figure 2.2: Modern pitot-static system and instruments for aircraft use. Figure adapted from Federal Aviation Administration (2016).
Figure 2.3: ED with a pitot-static probe. A schematic of the pitot-static probe is provided in the inset. Figure adapted from Bushnell et al. (1973).
Figure 2.4: Atypical GPS fall speed (red) and differential pressure indicated fall speed (blue) in m s$^{-1}$ for one dropsonde (1-D-5F4E) launched in Marty on 27 September 2015. Adapted from Nelson et al. (2019a).
Figure 2.5: Individual last data point fall speeds and altitudes from the data using M1. Panel (a) is the last data point GPS fall speeds of the dropsondes. Panel (b) is the altitude of the last data point in each sounding that reached at least 500 m. Also included are mean, maximum, minimum, median, and standard deviation.
Figure 2.6: Data points outside of convection used to derive the median dropsonde-parameter. Panel (a) is the last data point altitude. Panel (b) is the last data point fall speed. Panel (c) is the last data point density. Panel (d) is the dropsonde-parameter for each dropsonde launched outside of convection. Also included are mean, maximum, minimum, median, and standard deviation.
Figure 2.7: Box plot comparisons between M1, M2, M3, and M3b from Nelson et al. (2019a). The inset to the bottom right shows that the notches of the box plots do not overlap, which indicates that the medians are statistically different.
Figure 2.8: Polar plot of the pressure coefficient ($C_p$) at 10° angle of incidence intervals to the flow, 100 mph (pink) and 80 mph (purple). Figure adapted from Beck et al. (2010).
Figure 2.9: Vertical velocity soundings from sailplane and EDs with a pitot-static probe on 21 April 1972. Shown below each ED sounding is the mean difference in vertical velocity from the sailplane observations. Figure adapted from Bushnell et al. (1973).

Figure 2.10: Same as Fig. 2.9, but for 25 April 1972.
Figure 2.11: Sensitivity of vertical velocity of RD-94s due to changes in mass ($m_s$) (a, b), area ($A_s$) (c), and drag coefficient ($C_{ds}$) (d). Adapted from the appendix of Stern et al. (2016).
Figure 2.12: Errors in vertical velocity for XDDs given variations of mass (a), diameter/area (b), drag coefficient (c), and low-level updrafts (d), adapted from Nelson et al. (2019a).
Figure 2.13: Reynolds number ($R_e$) as a function of altitude for all 90 TCI XDDs launched outside of convection. A smoothing spline (green) is used to illustrate the general trend. The 17.5 km altitude cutoff is shown in red.
Figure 2.14: Design for a pitot-static system. Panel (a) is a generic schematic, where the pitot pressure ($P_1$) is greater than the static pressure ($P_2$), due to airflow (green arrows). The pressure transducer/membrane is the red square. Panel (b) illustrates a generic layout for a pitot-static system for the XDDs.
Figure 2.15: Design for a venturi-static system. Panel (a) is a generic schematic, where the static pressure (P1) is less than the venturi pressure (P2), due to airflow (green arrows). The pressure transducer/membrane is the red square. Panel (b) illustrates a generic layout for a venturi-static system for the XDDs.
Figure 2.16: Design for a pitot-venturi system. Panel (a) is a generic schematic, where the pitot pressure (P1) is greater than the venturi pressure (P2), due to airflow and the venturi effect (green arrows). The pressure transducer constriction of airflow is the red squares. Panel (b) illustrates a generic layout for a pitot-venturi system for the XDDs.
Figure 2.17: Visualization of wake flow behind a cylinder in axial flow with a length to diameter ratio of three. The x-axis and y-axis are normalized by the diameter of the cylinder. Figure is adapted from Higuchi et al. (2006).

Figure 2.18: Schematic for the DLHR-L05D-E1BD sensor including output/input pins and dimensions. Adapted from All Sensors (2019).
Out of the 785 total XDDs used in the 2015 TCI experiment, 725 were launched into Marty, Joaquin, and Patricia. This breaks down to 140, 328, and 257 XDDs for each TC, respectively. Marty was sampled as a tropical storm (sustained winds of 26 m s$^{-1}$) and a Category 1 hurricane (36 m s$^{-1}$) (Berg, 2016b). Joaquin was sampled as a Category 3 (57 m s$^{-1}$), Category 4 (67 m s$^{-1}$), Category 2 (47 m s$^{-1}$), and Category 1 (39 m s$^{-1}$) hurricane (Berg, 2016a). Patricia, ultimately, reached a higher peak intensity but was sampled as a tropical depression (15 m s$^{-1}$), tropical storm (26 m s$^{-1}$), Category 4 hurricane (59 m s$^{-1}$), and during rapid weakening from a Category 5 hurricane (92 m s$^{-1}$) (Kimberlain et al., 2016). Figure 3.1 shows the intensity for each of the three TCs from the National Hurricane Center (NHC) Best Track dataset and the time periods that they were observed during TCI.

Because of the unprecedented sounding spacing, altitude, frequency and the relative dearth of in-situ observations in TCs, this analysis is crucial to the future of dropsonde-derived vertical velocity studies. This analysis also offers a unique opportunity to: 1) document the convective structure of individual TCs from dropsondes alone; 2) study updrafts and downdrafts in unprecedentedly strong TCs like Patricia; 3) evaluate locations where dropsonde-derived vertical velocities and their errors have appreciable impact; 4) evaluate the role of vertical velocity in the calculation of horizontal wind; and 5) examine the impact of dropsonde spacing on the interpretation of the thermodynamic and kinematic structure and its impact on future dropsonde studies. Collectively, this chapter serves as documentation of the vertical velocities obtained using the M3 methodology discussed previously and further
illustrates the importance of accurate vertical velocity measurements from dropsonde.

3.1 Summary of TCI XDD-derived vertical velocities

3.1.1 Introduction

While convection in TCs is significantly weaker than in the midlatitudes (Jorgensen et al., 1985; Black et al., 1996; Heymsfield et al., 2010), the updrafts and downdrafts themselves, as well as their associated properties and sources, aid in driving intensity change in TCs. Deep-layer shear, and the subsequent asymmetric convection, can lead to short-term TC intensification with weakening thereafter (Kaplan and DeMaria, 2003; DeMaria et al., 2012). If there is sufficient energy provided to the TC from the ocean, the cyclone can resist the weakening effects of shear and maintain its strength or intensify (e.g., Black et al., 2002). Further, as deep, strong, convective updrafts are often located near the radius of maximum wind (RMW; Black et al., 1994; Rogers et al., 2013; Stern et al., 2016) or just inside the RMW (Jorgensen et al., 1985; Marks et al., 2008), they could be associated with intensification following RMW contraction (Stern et al., 2015).

One of the unresolved TC intensification processes is the role of small-scale vorticity and collocated updrafts in the vicinity of the eyewall. As described by Persing and Montgomery (2003), TCs can reach intensities higher than their maximum potential intensity (MPI) by mixing high-entropy air from the eye into the eyewall through vorticity maxima at the eye–eyewall interface. This process has been dubbed “superintensity” and has been supported observationally by the analysis of Montgomery et al. (2006). Bryan and Rotunno (2009), however, have shown that this process is inconsequential for a TC to reach its MPI. Regardless, intensity changes below the MPI of a TC due to eye–eyewall mixing (“sub-MPI intensity changes”; Eastin et al., 2005b) remain plausible and are supported by the findings
of Dolling and Barnes (2012).

It is not completely understood whether deep convection serves a critical role in the intensification of TCs. While many studies conclude that deep, strong convection is important (e.g., Steranka et al., 1986; Vigh and Schubert, 2009; Rogers et al., 2016), others argue that it is not (Jiang, 2012; Jiang and Ramirez, 2013). The discrepancies between these studies demonstrate the need for high-quality vertical velocity measurements and further study of TC convection. Furthermore, TC intensity forecasts have not substantially improved over the past decade (Pasch, 2011), suggesting that critical processes are not yet being captured by numerical simulations or observations.

Updrafts in excess of 10 m s$^{-1}$ have been observed occasionally in TCs, regardless of data source (Jorgensen et al., 1985; Black et al., 1994, 1996, 2002; Aberson et al., 2006; Marks et al., 2008; Heymsfield et al., 2010). Stern et al. (2016) and Stern and Aberson (2006) found that extreme updrafts ($\geq$ 10 m s$^{-1}$) were often collocated with low-level, extreme horizontal wind maxima ($\geq$ 90 m s$^{-1}$) in major hurricanes. Extremely strong vertical motions occur primarily in the upper-level eyewall (Black et al., 1996; Stern and Aberson, 2006; Aberson et al., 2006; Guimond et al., 2010). In many cases, the updrafts are a part of the asymmetric component of eyewall convection on top of the symmetric component (Eastin et al., 2005a,b; Guimond et al., 2010).

To date, radar, dropsonde, and flight-level data have found very few strong updrafts or downdrafts outside of 100 km from the storm center (e.g., Black et al., 1996) despite large amounts of lightning occurring in this region (Corbosiero and Molinari, 2002, 2003). This apparent discrepancy may be a result of limited samples at large radii, research and reconnaissance flights avoiding strong convection for safety, or relatively large radar volumes that cannot detect small scale convective features. Jorgensen et al. (1985) found that, above
1-km altitude, the top 10% of eyewall updraft cores are larger and stronger than rainband updrafts. While the eyewall embodies the primary ascending branch of the secondary circulation (Shapiro and Willoughby, 1982), convection outside of the eyewall can be excited by vortex Rossby waves (Black et al., 2002; Corbosiero et al., 2006) or consist of convective clouds stretched and deformed into intense banded structures (Moon and Nolan, 2015).

With respect to altitude, Black et al. (1994) found strong updrafts widely scattered in the mid- and lower-levels (2–6 km) of Hurricane Emily (1987), with small pockets of strong updrafts aloft (> 6 km). Other studies found that updraft strength increases with altitude (Jorgensen et al., 1985) and tends to maximize aloft between 10 and 15 km (Black et al., 2002; Heymsfield et al., 2010; Reasor et al., 2013; DeHart et al., 2014). Black et al. (1996) observed a relative minimum at 5–6 km in mean vertical velocity profiles. DeHart et al. (2014) found that strong updrafts in the core tended to occur aloft and primarily in the downshear-left quadrant. Downdrafts tended to occur aloft and in the midlevels in the upshear-left quadrant.

The most accepted, and supported, theory for updraft azimuthal and altitudinal distributions is that updrafts tend to initiate at low levels in the downshear-right quadrant and rise helically to their maximum intensity in the downshear-left quadrant, with downdrafts dominating the upshear quadrants, specifically the upshear-left quadrant (Franklin et al., 1993; Black et al., 2002; DeHart et al., 2014). Black et al. (2002), Zipser (2003), Stern and Aberson (2006), Guimond et al. (2010), Reasor et al. (2013), DeHart et al. (2014), and Stern et al. (2016) all show that updrafts maximize in strength in the downshear quadrants of the TC, especially the downshear-left quadrant in the core.

The most recent work on dropsonde-observed updrafts in TCs, Stern et al. (2016), had information for the radial, azimuthal, and altitudinal variances of updrafts in the lowest
2–3 km and examined updrafts that exceeded 10 m s$^{-1}$ only. The azimuthal, radial, and altitudinal XDD-derived vertical velocity distributions below 17.5 km from TCI flights into hurricanes Marty, Joaquin, and Patricia using the HDSS and XDDs (Doyle et al., 2017) were examined through the use of median vertical velocity profiles and contoured frequency diagrams. Bootstrap median significance tests were also conducted to examine statistical differences in the medians of positive and negative vertical velocities within specific sections of the TCs and are included in the Appendix. Basic characteristics of the observed updrafts and downdrafts from TCI were also examined.

3.1.2 Methods

The dropsonde-derived vertical velocities were calculated using the M3 methodology (Equations 2.9, 2.10, 2.12), with the hydrostatic, or differential pressure, fall speed (Equation 2.11) as $V_f$. The differential pressure fall speed was used in lieu of the GPS fall speed due to large, unrealistic discrepancies between the two fall speeds in the midlevels and aloft (e.g., Fig. 2.4) and because the accuracy of the pressure is better than GPS height derived fall speeds (Stern et al., 2016). This also matches the methodologies of Wang et al. (2015) and Stern et al. (2016). The differential pressure indicated fall speed was computed with a 15-point centered difference, after removing missing data, rather than from the Atmospheric Sounding Processing Environment (ASPEN) software (Bell et al., 2016), corresponding to a vertical depth of 750m at 17.5 km and 270m near sea-level, assuming there were no missing data points.

Dropsondes that were assumed to be launched outside of convection (see Section 2.3) were removed from the dataset. An example of IR brightness temperatures on 23 October in Patricia, with dropsondes launched outside of convection indicated by red circles, is provided.
in Figure 3.2. Soundings were also removed from the dataset if their last observed data point was at a GPS altitude greater than 500 m. The rationale for such a restriction was to ensure that the dropsondes recorded data in the low levels of TCs, comparable to Stern et al. (2016). The data were also restricted to only include data points below an altitude of 17.5 km. While the WB-57 was flown at an altitude of approximately 19 km, most dropsondes outside of convection take approximately 25 s to reach a stable fall speed after launch, a distance of 0.5 km to 1 km. The altitude restriction of 17.5 km was chosen to prevent erroneous data and provide an approximate 500 m buffer. Data were also restricted to within an RMW normalized radius, $R^*$, of 10 to eliminate data points that were well removed from the TC. The distances that correspond to $10R^*$ for each day are provided in Table 3.1.

The XDD-derived vertical velocities were then filtered using a nine-point binomial smoother. This corresponds to altitudinal depths of 162–450 m assuming no missing data. Spurious data points outside of two standard deviations of the local mean in the nine-point filter were removed after smoothing was completed. The total dataset was reduced to 276,515 data points and 437 soundings after all of the data restriction and removal were conducted.

Individual data points are used to create and analyze the vertical velocity frequency distributions but were not considered to be independent updrafts or downdrafts. Black et al. (1996) defined updrafts and downdrafts using Doppler radar data as consecutive, continuous vertical velocities exceeding $|1.5 \text{ m s}^{-1}|$ with at least one data point exceeding $|3 \text{ m s}^{-1}|$. The $|1.5 \text{ m s}^{-1}|$ threshold was chosen as it was outside the limits of uncertainty in the vertical incidence Doppler velocity and the $|3 \text{ m s}^{-1}|$ threshold was chosen as it was one standard deviation of hydrometeor fall speed above the limit of uncertainty (Black et al., 1996). Updrafts and downdrafts were similarly defined as consecutive, continuous vertical velocities exceeding $|2 \text{ m s}^{-1}|$ (limit of uncertainty, see Section 2.4) with at least one data
point exceeding $|4 \text{ m s}^{-1}|$ (one standard deviation of the vertical velocity above the limit of uncertainty).

The well-documented, high-resolution flight-level RMWs and Hurricane Research Division (HRD) centers were not used, because the flight-level data were rarely coincident with the TCI missions and HRD centers were not available for three of the ten observation days. Instead, the storm center was calculated using an iterative method similar to the methodologies of Creasey and Elsberry (2017) and Willoughby and Chemlow (1982) to find an estimated XDD-derived zero-wind center (ZWC). The dropsonde horizontal winds were corrected for storm motion by subtracting the $u$ and $v$ components of TC motion from the horizontal wind components. The TC motion was calculated by taking six-hour centered differences about the closest (in time) Automated Tropical Cyclone Forecast (AFTC) Best Track center from NHC. Comparisons of the flight-level RMWs and HRD centers to the RMWs and ZWCs used are provided in the Appendix, but the centers agree within a mean of approximately 17 km, the RMWs agree within a mean of 8–9 km, and the use of the flight-level RMWs and HRD centers do not produce statistically different results for the seven days of coverage.

A single ZWC was found by constructing orthogonal lines to the storm-motion-corrected horizontal wind vectors at all altitudes. Weighted means of the intersecting independent $(x, y)$ coordinates from pairs of observations yield a single ZWC estimate and corresponding time for the depth of the troposphere. The weighting function was:

$$W = \frac{V_i}{(r^2)},$$

where $W$ is the weight for a given intersection, $V_i$ is the mean storm-motion-corrected hor-
orizontal wind speed for any observation pair, and \( r \) is the mean radial distance of the observation pairs to the previous TC center estimate at the time of the observations. The initial ZWC estimate was taken to be the NHC Best Track center, linearly interpolated to the minute. As a consequence of the weighting-function dependence on the ZWC estimate, Equation 3.1 must be iterated to convergence. Iteration was done until the ZWC latitude and longitude converged on a single ZWC solution within 0.001° (approximately 100 m). All solutions converged within 18 iterations. The final ZWC is a single ZWC representative of the time of the observation with the highest weight. The final ZWC was also linearly interpolated to each minute of the observation period.

Rather than the traditional flight-level RMW, an estimated radius of maximum horizontal wind speed below an altitude of 2 km was calculated from the XDD horizontal wind data. The XDD-derived RMW was obtained by examining the strongest 99.98% of horizontal winds below 2 km and within a 100 km radius of the TC center. The RMW was approximated to be the mean radial distance of these relatively fast wind data points, rather than a single data point maximum. This averaging was done because a single data point may be unrepresentative of the true horizontal wind field of the TC, may be artificially strong due to turbulence or noise, or may not be appreciably different than other horizontal wind measurements at other radii. The 99.98% percentile was chosen iteratively to exclude secondary wind maxima within 100 km of the centers of the three TCs. The number of data points used to derive the RMW ranged from one to eight for each observation day, with most days having greater than five data points, corresponding to one to three soundings for each observation day with most days having only one RMW sounding.

An RMW was also calculated from overpasses of the Hurricane Imaging Radiometer (HIRAD; Cecil et al., 2016) as the radius with the strongest observed wind speed. For the
HIRAD RMWs, the TC center was taken to be the ZWC linearly interpolated to match the approximate center crossing, except for Joaquin. The ZWCs for Joaquin used here, and in Creasey and Elsberry (2017), differ from the HIRAD estimated center by approximately 5–7 km, potentially due to tilt of the TC. To alleviate this issue, the estimated HIRAD centers noted in Creasey and Elsberry (2017) were used to derive the HIRAD RMWs for Joaquin. Throughout the rest of this chapter, the RMWs used are the closest RMWs (derived from both the XDD data and the HIRAD data) to the Best Track dataset, which has an accuracy of approximately 9 km.

The 1800 UTC environmental shear was obtained from the Statistical Hurricane Intensity Prediction Scheme (SHIPS) dataset (DeMaria and Kaplan, 1994), as all flights were conducted near 1800 UTC. Data points were then analyzed in a shear-relative framework. Here, shear is defined conventionally (e.g., DeMaria and Kaplan, 1994) as the 850–200-hPa magnitude and direction with the vortex removed, and averaged from 0–500 km relative to the 850-hPa vortex center.

### 3.1.3 Results

Summarized in Table 3.1 is the number of viable dropsondes for each day in the full dataset. Also given are storm diagnostics including shear and intensity from SHIPS. As can be seen in Table 3.1, the dataset contained a strongly-sheared case (Marty), a moderately-sheared case (Joaquin), and a weakly-sheared case (Patricia). Joaquin was an Atlantic hurricane, while Marty and Patricia were in the eastern North Pacific. Most of the observation periods had a component of westerly shear and only Patricia on 21 October had easterly shear. It is also evident that the number of dropsondes after data exclusion was distributed evenly from day-to-day, except for 20 and 23 October.
Figure 3.3 shows the individual vertical velocity data points in a shear-relative framework within 10R* and 3R*. The downshear-right (DR) quadrant had the fewest observations: only 20% of the total vertical velocity data points. The upshear-right (UR) and upshear-left (UL) quadrants contained almost half of the data with 26% and 24% of the vertical velocity data points, respectively. The downshear-left (DL) contained 30%. Even though the majority of observations were outside of the RMW (approximately 80%), the area of the TC within the RMW had the highest number of data points per unit area, approximately 50 times more data points per unit area than outer radii (outside of 3R*). The area within 3R* is defined as the core following Rogers et al. (2013). Approximately 49% of the data was inside of the core.

3.1.3.1 Vertical profiles of vertical velocity

The mean vertical velocity values for the cores and outside of the cores of the three TCs agree well with the mean Doppler-derived vertical velocities for the eyewall and stratiform regions examined by Black et al. (1996) (Table 3.2). Mean, median, and standard deviation profiles of vertical velocity for all of the data, within the core, and outside of the core are provided in Figure 3.4. The mean profiles in vertical velocity for data inside and outside of the core also agree well with the Doppler vertical velocity profiles observed for the eyewall and stratiform regions in Black et al. (1996).

The median vertical velocity profiles were weaker than the mean vertical velocity profiles, but similar structures exist (Fig. 3.4a, b). The strongest vertical velocities were found aloft and within the core in both profiles (Fig. 3.4a, b), in agreement with the Doppler profiles observed by Black et al. (1996) despite XDD-derived vertical velocity errors increasing with altitude (see Appendix). Vertical velocities were positive for much of the depth of the
troposphere, but some negative vertical velocities were found below 5 km in the mean profile for data outside of the core (Fig. 3.4a), below 10 km in the median profile for data outside of the core (Fig. 3.4b), and below 5 km in the median profile for data within the core (Fig. 3.4b).

There was a notable peak in mean vertical velocity strength and standard deviation within the core just above the approximate freezing level at 5–6 km (Fig. 3.4a, c). It is not known if this spike is physically significant (e.g., Black et al., 1996; Heymsfield et al., 2010) or instrumentation errors due to icing. Regardless, the standard deviation of the vertical velocity was largest within the core, but fairly constant for data outside the core below 10 km (Fig. 3.4c).

Figures 3.5–3.8 show median vertical velocity profiles both inside (red) and outside (blue) of the core and within each shear-relative quadrant for Marty, Joaquin, Patricia, and for the total dataset. The approximate number of soundings within the core and outside of the core in each quadrant are also provided. These numbers are approximate because some soundings crossed quadrant boundaries. In those situations, the sounding was classified in the quadrant where it had the most data points. Statistical differences or statistical significances of the vertical velocity strength cannot be inferred directly from the median profiles, but they do agree well with bootstrap analysis and significance tests of the median vertical velocities (see Appendix). Mean profiles (not shown) show similar results as the median profiles.

Marty had large amplitude and noisy median vertical velocity profiles within the core in the DL quadrant and outside of the core in the DR quadrant (Fig. 3.5). This is likely a result of vertical variations in the vertical velocity data and a lack of samples (nine soundings and one sounding, respectively). The upshear profiles within the core and outside of the core
are consistent and similar to each other, with the weakest median vertical velocity profiles in the UL quadrant (Fig. 3.5). Joaquin had stronger and more positive median vertical velocity profiles in the DL and UR quadrants within the core above 6 km, and strong low-level positive vertical velocities in the left-of-shear quadrants within the core, especially the UL quadrant (Fig. 3.6). Patricia had strong upper-level positive vertical velocities in the DR quadrant, while the median vertical velocity profiles in the UR and DL quadrants were primarily weak and negative (Fig. 3.7). Similar to Marty, Patricia had a noisy vertical velocity profile within the core in the UL quadrant (Fig. 3.7), caused by three soundings near the eye that had strong variations in vertical velocity about zero. The combined dataset features positive upper-level vertical velocities above 7.5 km in the DL quadrant and negative vertical velocities below; positive vertical velocities below 13 km within the core in the DR quadrant; negative vertical velocities below 13 km outside of the core in the DR quadrant; and generally, weaker median vertical velocity profiles in the upshear quadrants (Fig. 3.8).

3.1.3.2 Contoured frequency diagrams

Contoured frequency diagrams with respect to radius (CFRD), shear-relative (SR) azimuth (CFAzD), and altitude (CFAD) are used to examine the XDD-derived vertical velocity distributions from TCI (Figs. 3.9–3.11). The contoured frequency plots were created for each TC as well as for the total dataset, with an altitudinal bin size of 250 m, a radial bin size of 0.5\(R^*\), and an azimuthal bin size of 10°. The bin sizes were chosen iteratively and subjectively. The vertical velocities were binned every 1 m s\(^{-1}\). Due to the shear-relative and radial biases in sampling, the contoured frequency plots are displayed as contoured percent diagrams, with a logarithmic scale. All percentages within any given bin (radial, azimuth, or altitudinal) sum to 100%. For reference, black horizontal lines in the contoured frequency
diagrams denote the vertical velocity thresholds used to define updrafts and downdrafts (|2 m s\(^{-1}\)| and |4 m s\(^{-1}\)|).

The peak vertical velocity strength generally decreased with increasing radius, and the radial distribution shows that positive vertical velocities more frequently exceeded the updraft thresholds than negative vertical velocities and the downdraft thresholds (Fig. 3.9d). The decrease in vertical velocity strength with increasing radius was not as prominent in Marty (Fig. 3.9a) as it was in Joaquin and Patricia (Fig. 3.9b, c). It should be noted, however, that negative vertical velocity magnitudes were much weaker than positive vertical velocity magnitudes, especially in Patricia (Fig. 3.9c) and exhibited less of a decrease in strength with increasing radius. Joaquin and Patricia had similar vertical velocity frequency distributions radially, especially for positive vertical velocities (Fig. 3.9b, c). Both TCs also had vertical velocity data points that exceeded 10 m s\(^{-1}\), which occurred at the RMW in Patricia and at approximately 3.5R* in Joaquin (not shown in the CFRDs).

For all storms and all radii (Fig. 3.10d), there was little azimuthal variation in the observed vertical velocity distribution, but the strongest vertical velocities were primarily observed in the right-of-shear quadrants. The lack of azimuthal variation in the vertical velocity distribution could be attributed to the relatively small sample size of three TCs or the asymmetric sampling during TCI (Fig. 3.3). The CFAzD for Marty (Fig. 3.10a) shows little azimuthal variation in the strongest negative vertical velocities, with most of the variation in the distribution occurring within the vertical velocity uncertainty bounds. The strongest positive vertical velocities in the distribution, however, were observed in the left-of-shear quadrants, especially the DL quadrant (Fig. 3.10a). The vertical velocity distributions of Joaquin and Patricia also show little systematic azimuthal variation (Fig. 3.10b, c), with sporadic peaks in frequency at different vertical velocity values. There was a decrease in
the vertical velocity strength, and frequency of vertical velocities above the updraft and
downdraft thresholds, in the upshear quadrants of Patricia (Fig. 3.10c).

The CFADs for all radii for each TC and the combined dataset are shown in Figure
3.11. Vertical velocity in the combined dataset was a weak function of altitude, with Figure
3.11d showing that the vertical velocity distribution broadens slightly aloft and becomes
skewed towards larger, more positive values. There was little altitudinal variation in the
CFAD for Marty, but the distribution was skewed towards positive vertical velocities, and
there were higher frequencies of negative vertical velocity below 5 km (Fig. 3.11a). The
altitudinal vertical velocity distribution in Joaquin was more centered around zero than in
Marty, but high percentages of negative values of approximately \(-1.5 \text{ m s}^{-1}\) were present
in Joaquin (Fig. 3.11b). Positive vertical velocities in Joaquin weakly increased in strength
aloft and negative vertical velocities were fairly uniform with altitude (Fig. 3.11b). Patricia
had a different altitudinal vertical velocity distribution than Marty or Joaquin (Fig. 3.11c).
The CFAD for Patricia shows that vertical velocity was skewed towards negative values,
especially within the uncertainty bounds, but there was more spread in the positive values
and little altitudinal signal (Fig. 3.11c).

CFRDs, CFAzDs, and CFADs for data within the core and outside of the core are
provided in the Appendix, but the results are summarized here. The CFAzDs and CFADs
for data within the core are not appreciably different from the total CFAzDs and CFADs.
The similarities between the contoured frequency diagrams for all radii and the contoured
frequency diagrams from the core reflect that the cores of the TCs have the most variation
and spread in the strength of the observed vertical velocities. The azimuthal distributions for
all three TCs outside of the core have higher frequencies of lower vertical velocity strength,
but little azimuthal variability exists in vertical velocity strength. There were very few data
points outside of the core in the DR or UR quadrants in Marty and in the DR quadrant in Joaquin due to sampling biases, which makes the distribution outside of the cores in Marty and Joaquin not robust. The CFADs for data outside of the core generally showed narrower vertical velocity distributions and more negative vertical velocities than the total CFADs, with differing altitudes of peak vertical velocity strength.

3.1.3.3 Updrafts and downdrafts

Table 3.3 shows the number of updrafts and downdrafts observed in the TCI subset soundings, as well as the means and medians of the maximum and minimum updraft and downdraft speeds. Given the small sample size of updrafts and downdrafts, robust conclusions about the convective asymmetries in the three TCs cannot be made, but the examination of the updrafts and downdrafts observed is useful in understanding the TCI vertical velocity dataset. Patricia had the strongest observed mean and median updraft speeds, the strongest peak updraft strength at 23.89 m s⁻¹, and was the only TC to have a low-level updraft (below 2 km) with a maximum value exceeding 10 m s⁻¹. Downdraft speeds were more comparable between the three TCs, with the strongest downdraft in Joaquin at −8.7 m s⁻¹. Most updrafts and downdrafts observed during TCI had mean and median strengths of approximately |3–4| m s⁻¹, and maximum strengths of approximately |4–5| m s⁻¹. Updraft and downdraft depths were primarily less than 4 km with 50% of the updrafts and downdrafts smaller than 1.2–1.4 km.

Shown in Figures 3.12–3.14 are select “cross sections” of vertical velocity with updrafts and downdrafts contoured. It is important to note that the cross sections presented here are not true cross sections, because the dropsondes drift around the TC in a cyclonic trajectory. Each data point corresponds to a unique altitude and distance from the center to account for
radial drift of the dropsonde during descent. The strongest vertical velocities and updrafts in Marty on 27 September were aloft, above 12 km in the eyewall (inner 30–40 km; Fig. 3.12). There were weaker bands of positive and negative vertical velocities outside of the eyewall to the northwest of the TC center (Fig. 3.12). Joaquin on 2 October was at a stronger intensity than Marty on 27 September and had considerably stronger and deeper eyewall updrafts than Marty at approximately 8 m s\(^{-1}\) (Fig. 3.13). Joaquin on 2 October also exhibited an asymmetric distribution in the eyewall convection (e.g., Fig. 3.13). The strongest eyewall convection was towards the southeast of TC center, which is on the downshear side of the storm (Fig. 3.13).

The vertical velocity cross section on 23 October in Patricia shows deep, strong low-level and mid-level eyewall updrafts greater than 10 m s\(^{-1}\) (Fig. 3.14a, b). Patricia also had a low-level updraft that exceeded 10 m s\(^{-1}\) collocated with a localized azimuthal wind maximum (Fig. 3.14b) and apparent radial overturning circulation (Fig. 3.14c) in the vicinity of a secondary eyewall observed in HIRAD data (Fig. 3.15), which supports the numerical simulations by Hazelton et al. (2017). The low-level radial overturning circulation was sampled by six soundings spaced 5–11 km apart with small radial (approximately 18–300 m) and azimuthal (approximately 1–2 km) drifting below 2 km. The spacing of the last data points of the soundings also did not deviate drastically from their spacing at 2 km. The relatively small radial and azimuthal motions, and small spacing deviations of the soundings below 2 km, do not severely impact the interpretation of the low-level cross section in Figure 3.14c and indicates that the radial overturning circulation is real and not a manifestation of sounding issues. It cannot be concluded with absolute certainty, however, that the low-level radial circulation and the strong low-level updraft were directly associated with the secondary eyewall. The radial overturning circulation and low-level updraft were
also collocated if the high-resolution HRD center was used instead of the XDD-derived ZWC.

Patricia also had a $\pm 2 \text{ m s}^{-1}$ amplitude wave-like feature in the vertical velocity on 23 October near 17 km with a wavelength of approximately 20–30 km. This apparent wave-like feature is in the same approximate location to where Duran and Molinari (2018) found a potential gravity wave at a comparable wavelength (Fig. 3.14d, e). The potential gravity wave is visible in both pressure (Fig. 3.14d) and potential temperature (Fig. 3.14e) at a wavelength of 20–30 km. The agreement between both studies, and the agreement between the wave-like feature in the vertical velocity to pressure and potential temperature, further supports that the XDDs sampled a gravity wave in Patricia on 23 October.

3.1.4 Discussion

Examining the altitudinal, azimuthal, and radial frequency distributions of vertical velocity, as well as the strength of the vertical velocity, serves a critical role in understanding the kinematic and convective environments of the TCs observed during TCI. The results presented here are a preliminary step at evaluating dropsonde-derived vertical velocities from the XDDs in TCs. The unprecedented high temporal and spatial resolution of these dropsondes during TCI allowed for analysis of the vertical velocities in Marty, Joaquin, and Patricia. These results serve as documentation of the strength and location of vertical velocities observed during TCI.

From the large datasets of RD-93 and RD-94 data, it has been shown that low-level ($< 3 \text{ km}$) updrafts greater than 10 m s$^{-1}$ occur exclusively in major hurricanes (Stern et al., 2016). Out of the 437 dropsondes (276,515 data points), only 719 vertical data points had vertical velocities greater than 10 m s$^{-1}$ (0.3% of the data), only 12 unique updrafts had maximum vertical velocities greater than 10 m s$^{-1}$, and only two of the positive vertical
velocity data points below 3 km reached 10 m s\(^{-1}\). The two data points were within a low-level updraft with collocated horizontal winds of 42 m s\(^{-1}\) and an overturning circulation in Patricia on 23 October as a major hurricane, but during rapid weakening (Figs. 3.14 and 3.15). At the same time, a potential upper-level gravity wave was observed in the vertical velocity, pressure, and potential temperature fields (Figs. 3.14). The strongest downdrafts, however, were not observed in Patricia, but in Joaquin.

The results show that vertical velocity strength, updraft strength, and downdraft strength are all strongest within the core (Figs. 3.9 and 3.4–3.8) and is also supported by comparisons of CFADs and CFAzDs for data within the core and outside of the core (see Appendix). Evidence of stronger, positive mean and median vertical velocities were also found aloft for the entire dataset and within most shear quadrants in all three TCs (Figs. 3.4–3.8), which agrees with the findings of Jorgensen et al. (1985), Black et al. (1996), Black et al. (2002), Zipser (2003), Heymsfield et al. (2010), Reasor et al. (2013), and DeHart et al. (2014) that utilized flight-level or Doppler-radar data. The CFADs either do not illustrate this characteristic or do not illustrate it as strongly as the CFADs in Black et al. (1996). For example, the 0.0625–8% frequency contours for positive vertical velocity in Joaquin broaden with height to varying degrees (Fig. 3.11b), but not as strongly as observed in Black et al. (1996).

The TCI XDD CFADs and Black et al. (1996) may differ because: 1) vertical velocity errors are largest aloft (see Appendix); 2) dropsonde fall stability is likely a larger issue aloft; 3) there are three TCs observed in TCI and seven TCs in Black et al. (1996); 4) the use of a differential pressure fall speed rather than the GPS fall speed produces weaker vertical velocities aloft (see Appendix); 5) TC intensity, rate of intensity change, and time relative to peak intensity or rapid intensification can cause differences in CFADs (McFarquhar et al.,
6) CFAD profiles can vary from storm-to-storm (Nguyen et al., 2017); 7) lack of radar data aloft and the use of a minimum reflectivity threshold drastically changes TC CFADs in the upper levels (McFarquhar et al., 2012; Nguyen et al., 2017); and, 8) if the true geometric center of an updraft or downdraft is not sampled, then vertical velocity may be underestimated for the updraft or downdraft (Jorgensen et al., 1985). The TCI XDD CFADs more resemble the rainband and stratiform CFADs from Black et al. (1996) than the eyewall CFAD (Fig. 3.11). The CFADs do resemble the CFAD from simulations of Dennis (2005) near rapid intensification, but without a minimum reflectivity threshold (McFarquhar et al., 2012). Further, the similarities between the mean and median values (Table 3.2), profiles (Figs. 3.4–3.8), and the results in Black et al. (1996) provide support and increase confidence in the quality of the XDD-derived TCI vertical velocity dataset.

The azimuthal vertical velocity distributions (Fig. 3.10) do not show robust patterns and do not agree well with the canonical wavenumber-one convective asymmetry within the core (e.g., Black et al., 2002; Corbosiero and Molinari, 2002, 2003; Stern and Aberson, 2006; Guimond et al., 2010; Reasor et al., 2013; DeHart et al., 2014). It is possible that the convection was organized by vortex tilt rather than the 850–200-hPa shear (e.g., Stevenson et al., 2014). This discrepancy and lack of data, especially at outer radii, suggest that more observations with an even distribution of samples in each shear-relative quadrant are likely required to analyze dropsonde-derived convective asymmetries in individual TCs using CFAzDs. Bootstrap analysis provided in the Appendix, however, suggests that Marty had the strongest median XDD-derived vertical velocities in the DL quadrant within the core, but the lack of data in each shear-relative quadrant make the finding unrobust. It is also important to remember that the CFAzDs are used to look at the azimuths with the highest frequency of vertical velocity, which can lead to discrepancies. For example, it is possible that
a quadrant could have a relatively higher frequency of vertical velocities at an appreciable strength, but the mean or median strength within the quadrant may be considerably weaker.

In order to better understand dropsonde-derived vertical velocities, the errors associated with the calculation of vertical velocity need to be addressed. If GPS fall speeds are used in the calculation of vertical velocity, strict screening of the data must be conducted to remove large, unrealistic errors in the fall speed like in Figure 2.4. If a maximum difference of 1 m s\(^{-1}\) between the GPS fall speed and the hydrostatic differential pressure fall speed is allowed, then 40,168 data points from the subset TCI soundings would need to be removed or quality controlled. Stern et al. (2016) note, however, that using the differential pressure fall speed alone may introduce errors when examining extreme non-hydrostatic updrafts.

This serves as justification for this dissertation and the improvement of the measurement of dropsonde fall speed and the decrease in dropsonde fall speed errors. As shown in Section 2.4, dropsonde-derived vertical velocity errors using any of the drag force methods are approximately ±1–2 m s\(^{-1}\). Dropsonde-derived vertical velocity errors an order of magnitude smaller would improve the confidence of the vertical velocities between ±2 m s\(^{-1}\), which accounts for a large portion of the vertical velocity distributions in TCs (e.g., Black et al. (1996) and Figs. 3.9–3.11). Vertical velocity errors within the 1-2 m s\(^{-1}\) range also impact the ability to observe gravity wave features aloft in TCs like in Patricia on 23 October (Fig. 3.14).
Table 3.1: Number of dropsondes from each day in the dataset \((N_t)\). \(S\) is the deep-layer shear \((850–200 \text{ hPa})\) in m s\(^{-1}\) and \(S_D\) is the shear direction in degrees clockwise from the north \(^\circ\). Intensity is the maximum tangential wind speed in m s\(^{-1}\) at 1800 UTC from the SHIPS dataset. The 10R\(^\ast\) distances in km for each day is also provided. From Nelson et al. (2019a).

<table>
<thead>
<tr>
<th>Day</th>
<th>Name</th>
<th>(N_t)</th>
<th>Intensity</th>
<th>(S)</th>
<th>(S_D)</th>
<th>10R(^\ast)</th>
</tr>
</thead>
<tbody>
<tr>
<td>27 Sept</td>
<td>Marty</td>
<td>50</td>
<td>26</td>
<td>11.21</td>
<td>98</td>
<td>370</td>
</tr>
<tr>
<td>28 Sept</td>
<td>Marty</td>
<td>58</td>
<td>36</td>
<td>11.00</td>
<td>89</td>
<td>210</td>
</tr>
<tr>
<td>02 Oct</td>
<td>Joaquin</td>
<td>44</td>
<td>57</td>
<td>4.90</td>
<td>151</td>
<td>310</td>
</tr>
<tr>
<td>03 Oct</td>
<td>Joaquin</td>
<td>43</td>
<td>67</td>
<td>13.20</td>
<td>127</td>
<td>270</td>
</tr>
<tr>
<td>04 Oct</td>
<td>Joaquin</td>
<td>55</td>
<td>44</td>
<td>4.90</td>
<td>66</td>
<td>380</td>
</tr>
<tr>
<td>05 Oct</td>
<td>Joaquin</td>
<td>53</td>
<td>39</td>
<td>3.90</td>
<td>39</td>
<td>490</td>
</tr>
<tr>
<td>20 Oct</td>
<td>Patricia</td>
<td>12</td>
<td>15</td>
<td>5.25</td>
<td>42</td>
<td>770</td>
</tr>
<tr>
<td>21 Oct</td>
<td>Patricia</td>
<td>51</td>
<td>26</td>
<td>2.93</td>
<td>195</td>
<td>400</td>
</tr>
<tr>
<td>22 Oct</td>
<td>Patricia</td>
<td>43</td>
<td>59</td>
<td>0.62</td>
<td>146</td>
<td>190</td>
</tr>
<tr>
<td>23 Oct</td>
<td>Patricia</td>
<td>28</td>
<td>93</td>
<td>4.58</td>
<td>21</td>
<td>110</td>
</tr>
<tr>
<td>TOTAL</td>
<td></td>
<td>437</td>
<td>46 (avg)</td>
<td>6.25 (avg)</td>
<td></td>
<td>350 (avg)</td>
</tr>
</tbody>
</table>

Table 3.2: Mean, median, and standard deviation of vertical velocity in m s\(^{-1}\) for all radii, within the core, and outside of the core. From Nelson et al. (2019a).

<table>
<thead>
<tr>
<th>Section</th>
<th>Mean</th>
<th>Median</th>
<th>St. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>0–10R(^\ast)</td>
<td>0.20</td>
<td>0.00</td>
<td>1.43</td>
</tr>
<tr>
<td>0–3R(^\ast)</td>
<td>0.30</td>
<td>0.06</td>
<td>1.74</td>
</tr>
<tr>
<td>3–10R(^\ast)</td>
<td>0.09</td>
<td>−0.04</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Table 3.3: Number of updrafts and downdrafts from each TC \((N)\) and the mean, median, and maximum/minimum of the peak updraft and downdraft strengths in m s\(^{-1}\). From Nelson et al. (2019a).

<table>
<thead>
<tr>
<th>Updrafts</th>
<th>Name</th>
<th>(N)</th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Marty</td>
<td>17</td>
<td>5.11</td>
<td>4.90</td>
<td>7.23</td>
</tr>
<tr>
<td></td>
<td>Joaquin</td>
<td>48</td>
<td>5.91</td>
<td>5.11</td>
<td>18.33</td>
</tr>
<tr>
<td></td>
<td>Patricia</td>
<td>38</td>
<td>8.72</td>
<td>6.77</td>
<td>23.89</td>
</tr>
<tr>
<td></td>
<td>TOTAL</td>
<td>103</td>
<td>6.58 (avg)</td>
<td>5.59 (avg)</td>
<td>16.48 (avg)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Downdrafts</th>
<th>Name</th>
<th>(N)</th>
<th>Mean</th>
<th>Median</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Marty</td>
<td>9</td>
<td>−5.15</td>
<td>−5.16</td>
<td>−5.90</td>
</tr>
<tr>
<td></td>
<td>Joaquin</td>
<td>24</td>
<td>−5.40</td>
<td>−4.81</td>
<td>−8.70</td>
</tr>
<tr>
<td></td>
<td>Patricia</td>
<td>10</td>
<td>−4.54</td>
<td>−4.29</td>
<td>−5.95</td>
</tr>
<tr>
<td></td>
<td>TOTAL</td>
<td>43</td>
<td>−5.03 (avg)</td>
<td>−4.75 (avg)</td>
<td>−6.85 (avg)</td>
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</table>
Figure 3.1: Observed NHC Best Track intensity (m s$^{-1}$) for Marty (a), Joaquin (b), and Patricia (c) over time (month, day, hour). Periods when TCI observed the TCs are shaded in red. From Nelson et al. (2019a).
Figure 3.2: IR satellite image of Patricia at 2045 UTC 23 October 2015. Brightness temperatures (°C) are shaded. Launch locations for soundings outside of convection (red), soundings removed from the dataset by quality control or radial restriction (black diamonds), and soundings analyzed (blue) are also included. IR image courtesy of David Vollaro. From Nelson et al. (2019a).
Figure 3.3: Distribution of data points in the total dataset in a shear-rotated framework. Azimuth is in degrees and radius is the radius divided by the RMW (R*). The RMW is the green ring. Panels (a, c) are plotted out to 10R* and panels (b, d) are plotted out to 3R*. Continuous positive vertical velocities within updrafts are in red in panels (a, b) and continuous negative vertical velocities within downdrafts are in blue in panels (c, d). From Nelson et al. (2019a).
Figure 3.4: Mean (a), median (b), and standard deviation (c) profiles of vertical velocity for the full dataset (black), data within the core (red), and data outside of the core (blue). The dashed black line designates \( w = 0 \) m s\(^{-1}\). From Nelson et al. (2019a).
Figure 3.5: Median vertical velocity profiles for data within the core (red) and outside of the core (blue) and within the DL (a), DR (b), UL (c), and UR (d) quadrants in Marty. The dashed black line designates $w = 0 \text{ m s}^{-1}$. The approximate number of soundings in each quadrant is provided for within the core (red) and outside of the core (blue). From Nelson et al. (2019a).
Figure 3.6: Same as Fig. 3.5, but for Joaquin. From Nelson et al. (2019a).
Figure 3.7: Same as Fig. 3.5, but for Patricia. From Nelson et al. (2019a).
Figure 3.8: Same as Fig. 3.5, but for the total dataset. From Nelson et al. (2019a).
Figure 3.9: CFRD percentages of vertical velocities (m s$^{-1}$). Panel (a) is for Marty, panel (b) is for Joaquin, panel (c) is for Patricia, and panel (d) is for the entire dataset. Colored contours are percentages on a logarithmic scale. Black lined contours are percentages above 20% in intervals of 5%. The horizontal solid black lines denote the vertical velocity thresholds. The dashed white line designates $w = 0$ m s$^{-1}$. From Nelson et al. (2019a).
Figure 3.10: CFAzD percentages of vertical velocities (m s\(^{-1}\)). Panel (a) is for Marty, panel (b) is for Joaquin, panel (c) is for Patricia, and panel (d) is for the entire dataset. Colored contours are percentages on a logarithmic scale. Black lined contours are percentages above 20% in intervals of 5%. The horizontal solid black lines denote the vertical velocity thresholds. The dashed white line designates \( w = 0 \) m s\(^{-1}\). From Nelson et al. (2019a).
Figure 3.11: CFAD percentages of vertical velocities (m s\(^{-1}\)). Panel (a) is for Marty, panel (b) is for Joaquin, panel (c) is for Patricia, and panel (d) is for the entire dataset. Colored contours are percentages on a logarithmic scale. Black lined contours are percentages above 20% in intervals of 5%. The horizontal solid black lines denote the vertical velocity thresholds. The dashed white line designates \( w = 0 \) m s\(^{-1}\). From Nelson et al. (2019a).
Figure 3.12: Transect cross section for Marty on 27 September. Panel (a) is a cross section of vertical velocity (m s\(^{-1}\), shaded) with vertical velocities greater than \(|2\ \text{m s}^{-1}|\) contoured. Panel (b) is a cross section of vertical velocity (m s\(^{-1}\), shaded) and horizontal wind speed (m s\(^{-1}\), contoured). The TC center is denoted with a solid vertical black line. From Nelson et al. (2019a).

Figure 3.13: Same as Fig. 3.12, but for Joaquin on 02 October. From Nelson et al. (2019a).
Figure 3.14: Transect cross section for Patricia on 23 October. Panel (a) is a cross section of vertical velocity ($m \ s^{-1}$, shaded), with vertical velocities greater than $|2 \ m \ s^{-1}|$ contoured. Panel (b) is a cross section of vertical velocity ($m \ s^{-1}$, shaded) and horizontal wind speed ($m \ s^{-1}$, contoured). Panel (c) is a low-level zoom-in of panel (a) showing vertical velocity ($m \ s^{-1}$, shaded) and radial velocity ($m \ s^{-1}$, contoured), where inflow is negative and outflow is positive. An upper-level zoom-in of panel (a) for vertical velocity ($m \ s^{-1}$, contoured) and pressure (hPa, contoured) is shown in panel (d). An upper-level zoom-in of panel (a) for vertical velocity ($m \ s^{-1}$, contoured) and potential temperature (K, contoured) is shown in panel (e). From Nelson et al. (2019a).
Figure 3.15: HIRAD-derived horizontal wind speeds for a transect over the center of Patricia on 23 October. Sounding trajectories are plotted in black and data points that sampled the low-level radial circulation are plotted in red. From Nelson et al. (2019a).
3.2 Wind finding equations

3.2.1 Introduction

While this dissertation is focused on addressing dropsonde-derived vertical velocity methods, accuracies, and errors, accurate horizontal wind speeds are also important in depicting and documenting TC structure. While it is unlikely that dropsondes sample the most extreme horizontal wind speeds (e.g., Stern and Bryan, 2018), as they are difficult to use to identify the RMW (Section 3.1; Cecil and Biswas, 2017), dropsondes are useful for depicting the strong horizontal wind fields within the hurricane boundary layer (Franklin et al., 2003). These horizontal wind observations are also important in analyzing features associated with deep, strong convection within TCs (Aberson et al., 2006; Stern et al., 2016; Stern and Bryan, 2018), documenting TC outflow and the strength of the warm core (e.g., Komaromi and Doyle, 2017), analyzing turbulence (Li and Miller, 2014a,b), and creating composite radial and azimuthal wind profiles (Giammanco et al., 2013). For example, Figure 3.14 depicts a strong updraft that was associated with the radial overturning circulation of a secondary eyewall that occurred in Patricia on 23 October.

As GPS chip sets improve, so do the reported horizontal position and velocity accuracies. Past dropsonde studies using the Vaisala RD-93s, RD-94s, or XDDs have noted horizontal wind accuracies or error estimates between 0.1 m s$^{-1}$ and 0.5 m s$^{-1}$ (Hock and Franklin, 1999; Wang et al., 2015; Black et al., 2017). The u-blox 6 GPS chip used on the XDDs during TCI is claimed to have a velocity accuracy of 0.1 m s$^{-1}$ at a circular error probability of 50% (U-blox, 2019). Accuracies of 0.05 m s$^{-1}$, however, may be possible if the GPS chip was upgraded to the new u-blox 8 (U-blox, 2019).

Despite the increased position and velocity accuracies in radiosonde or dropsonde GPS
chip sets, inaccuracies exist in the methods used to calculate the horizontal wind speed. One of the most rudimentary methods for calculating the horizontal wind is to assume that the horizontal wind components \((u, v)\) are equal to the horizontal motion components \((\dot{x}, \dot{y})\) of the radiosonde/dropsonde (Hock and Franklin, 1999; Houchi et al., 2015). This incorrectly assumes that: 1) the dropsonde can be considered as a spherical point; 2) the dropsonde accommodates immediately to the horizontal wind; 3) the dropsonde accommodates immediately to the local wind shear; and 4) there are no appreciable vertical or horizontal accelerations of the dropsonde motion speed. This method will, hereafter, be referred to as the xy-methodology.

Hock and Franklin (1999), hereafter referred to as HF99, derived a set of equations, commonly referred to as the ‘wind-finding equations’ (WFEs), to calculate the horizontal wind components from the position information of a falling object in the presence of wind shear. In their calculations, they assume that: 1) the dropsonde can be considered as a spherical point; 2) the dropsonde accommodates immediately to the wind shear; 3) the magnitude of the difference between the true horizontal wind and the dropsonde motion is small compared to the difference between the true vertical wind and the dropsonde fall speed; 4) the vertical velocity is negligible; 5) the Coriolis parameter can be neglected; and 6) the vertical acceleration of the dropsonde motion is small compared to the gravitational force. The HF99 methodology is an improvement upon the rudimentary xy-methodology, because it accounts for the dropsonde fall speed and the ratio of the horizontal accelerations to the downward gravitational acceleration.

Li and Miller (2014a), hereafter referred to as LM14a, note that vertical velocity cannot be ignored or cancelled when dropsondes are launched operationally into convection. In some cases, the dropsonde may stall or ascend and the horizontal motion of the dropsonde more
closely matches the true horizontal wind (LM14a). LM14a still assumes, however, that the magnitude of the difference between the true horizontal wind and the dropsonde motion is small compared to the difference between the true vertical wind and the dropsonde fall speed. This assumption may not hold in the situations they cite, where the dropsonde fall speed is approximately equal to the vertical wind speed. In that case the magnitude of the difference between the true horizontal wind and the dropsonde motion may be comparable to the difference between the true vertical wind and the dropsonde fall speed. LM14a use their version of the WFEs to find analytical solutions to depict dropsonde-observed turbulence.

The HF99 and LM14a WFE methodologies were derived, analyzed, and optimized for simple calculations of $u$ and $v$ for the Vaisala RD-93 and RD-94 dropsondes, which have parachutes. Unlike these dropsondes, the XDDs do not have parachutes and fall at much faster rates than the RD-93s and RD-94s (Black et al., 2017). Because of their fast, ballistic fall trajectories, the standard xy-methodology is likely not the optimum or most accurate method to compute horizontal winds for the XDDs. The HF99 and LM14a methodologies both contain major assumptions that do not hold in convective environments, such as the inner core of a TC, and, therefore, may not be true for the XDDs. The xy-, HF99, and LM14a methodologies were used to compute horizontal winds using data from the TCI dataset. An alternative method to compute the horizontal wind using a more complete equation set was also analyzed.

### 3.2.2 Methods

#### 3.2.2.1 Governing equations

From the governing equations for a falling object, derived below, there are four methods for calculating the horizontal winds using dropsondes: 1) the xy-method (Equations 3.18,
3.19); 2) the HF99 WFEs (Equations 3.16, 3.17); 3) the LM14a WFEs (Equations 2.9, 3.14, 3.15); and 4) the full WFEs (Equations 2.9, 3.12, 3.13). This section summarizes the derivation of the four equation sets starting from Newton’s second law:

\[ \vec{F} = m\vec{a} \]  
\[ \vec{F} = ma_x\hat{i} + ma_y\hat{j} + ma_z\hat{k} \]  
\[ \ddot{a} = \ddot{g} + \frac{C_d\rho A\vec{V} \cdot |\vec{V}|}{2m} \]  
\[ a_x = \frac{C_d\rho A V_x |\vec{V}|}{2m} \]  
\[ a_y = \frac{C_d\rho A V_y |\vec{V}|}{2m} \]  
\[ a_z = g + \frac{C_d\rho A V_z |\vec{V}|}{2m} \]

where \( \vec{V} \) is the three-dimensional motion-relative wind vector. It should be noted that the true drag coefficient for any dropsonde is not likely to be uniform. The dropsonde horizontal drag coefficient may be larger than the vertical (nose into the flow) drag coefficient. Computational fluid dynamics simulations of the XDDs in axial and radial flow using the \textit{simFlow} software (see Chapter 4) suggest that \( C_d \) varies from 0.93 (axial) and 1.28 (radial), respectively. The relative uniformity of \( C_d \) for the XDDs with respect to angle of incidence

80
to the flow is due to the similar ratios of drag force to area in the model and implies that
the uniform drag coefficient assumption is not likely to introduce large errors when using the
XDDs. This assumption may not be true for other dropsondes that use parachutes.

If equations 3.5, 3.6, and 3.7, are expanded, the following equations are obtained:

\begin{equation}
m \ddot{x} = 0.5 \rho C_d A (u - \dot{x}) \sqrt{(u - \dot{x})^2 + (v - \dot{y})^2 + (w - \dot{z})^2} \tag{3.8}
\end{equation}

\begin{equation}
m \ddot{y} = 0.5 \rho C_d A (v - \dot{y}) \sqrt{(u - \dot{x})^2 + (v - \dot{y})^2 + (w - \dot{z})^2} \tag{3.9}
\end{equation}

\begin{equation}
m \ddot{z} = mg + 0.5 \rho C_d A (w - \dot{z}) \sqrt{(u - \dot{x})^2 + (v - \dot{y})^2 + (w - \dot{z})^2} \tag{3.10}
\end{equation}

where \( \ddot{x}, \ddot{y}, \text{ and } \ddot{z} \) are the dropsonde acceleration components. Equation 3.10 can be re-
arranged as:

\begin{equation}
\frac{0.5 \rho C_d A}{m} = \frac{(\ddot{z} - g)}{(w - \dot{z}) \sqrt{(u - \dot{x})^2 + (v - \dot{y})^2 + (w - \dot{z})^2}} \tag{3.11}
\end{equation}

If equation 3.11 is plugged into equations 3.8 and 3.9, and re-arranged to solve for \( u \) and \( v \), an equation set is obtained to compute the horizontal wind components.

\begin{equation}
u = \frac{\ddot{x} (w - \dot{z})}{(\ddot{z} - g)} + \ddot{x} \tag{3.12}
\end{equation}

\begin{equation}
v = \frac{\ddot{y} (w - \dot{z})}{(\ddot{z} - g)} + \ddot{y} \tag{3.13}
\end{equation}

Using the assumptions of LM14a, equations 3.12 and 3.13 can be simplified to be:
\[
u = \left| \frac{w}{g} \ddot{x} - \frac{\dot{z}}{g} \right| + \dot{x}
\]

(3.14)

\[
v = \left| \frac{w}{g} \ddot{y} - \frac{\dot{z}}{g} \right| + \dot{y}
\]

(3.15)

If it is assumed that \(\ddot{x}\) and \(w\) are zero, however, the equations reduce to the HF99 WFEs.

\[
u = -\frac{\dot{z}}{g} \ddot{x} + \dot{x}
\]

(3.16)

\[
v = -\frac{\dot{z}}{g} \ddot{y} + \dot{y}
\]

(3.17)

A form of the HF99 WFEs is commonly used in the Atmospheric Sounding Processing Environment (ASPEN) software for quality controlling dropsonde data (Bell et al., 2016). If it is further assumed that there are no horizontal accelerations of the dropsonde, equations 3.16 and 3.17 reduce to the xy-method equations.

\[
u = \dot{x}
\]

(3.18)

\[
v = \dot{y}
\]

(3.19)

Equations 3.12 and 3.13 indicate that by increasing the accuracy of the dropsonde GPS position and dropsonde horizontal velocity, the accuracy of \(u\) and \(v\) should increase. Another consequence of equations 3.12 and 3.13 is that by increasing the accuracy of vertical
velocity and dropsonde fall speed, the accuracy of $u$ and $v$ should increase, which further motivates this dissertation. It also supports further analysis of dropsonde-derived vertical velocity errors and the addressing ways to improve the measurements.

HF99 calculated vertical velocity by subtracting the true observed fall speed from a theoretical, quiescent environment, still air fall speed. If it is assumed that $w$ is zero and the dropsonde is falling at terminal speed ($\ddot{z}$ equals zero), then the $u$ and $v$ wind components equal the horizontal motion of the dropsonde. In this situation, equation 3.11 is reduced to equation 2.9 (Chapter 2). HF99 note that the differences between the full WFE horizontal winds and their WFE horizontal winds are small and on the order of 0.5 m s$^{-1}$. It is unknown if these small differences are comparable for the XDDs or if they are larger/smaller in the convective environments of a TC.

### 3.2.2.2 Data

A total of 725 XDDs were launched into Marty, Joaquin, and Patricia, but the horizontal wind was calculated using the four equation sets for only 631 XDD of the soundings from the TCI experiment, because they terminated below an altitude of 500 m. This 500 m restriction was used to ensure that soundings contained data within the low levels of the TCs comparable to Stern et al. (2016). Note that the $R^*$ restriction used in Section 3.1 was not used in this section in order to compare the four WFE methods both within the TCs and within the environments outside of the TCs. Data were restricted to below 17.5 km due to dropsonde kinematic adjustments upon launching from the aircraft at 19 km. The TC centers and RMWs were the same as in Section 3.1 and vertical velocity was computed from using the M3 methodology.

The latitude, longitude, altitude, vertical velocity, dropsonde velocity, and dropsonde
acceleration were smoothed using a nine-point binomial smoother, and anomalous data points outside of two standard deviations of the local mean in the nine-point filter were removed. After all data removal and data restriction, a total of 376,717 horizontal wind data points were compared. In an effort to estimate the utility of using any version of the higher-order WFEs, the HF99, LM14a, and full WFE methodology horizontal winds are compared to the xy-method horizontal winds. In addition, the full WFE methodology horizontal winds are compared to the others to demonstrate the utility of using the full, "un-approximated," equation sets to obtain the horizontal wind. For the sake of brevity, the xy-method, HF99 method, LM14a method, and full WFE method is abbreviated as V1–V4, respectively, in all plots.

### 3.2.3 Results

Figure 3.16 shows two sample soundings of horizontal wind from a non-convective (NC) region of Marty on 28 September and a highly convective region (C) of Patricia during rapid decay on 23 October. The designation of NC versus C is qualitative, but is supported by the strength of vertical velocity in the profile (Fig. 3.17), the infrared brightness temperatures (Fig. 3.18), and the distance from the eye. The sounding from Marty on 28 September had a mean $R^*$ of approximately nine and a mean distance of approximately 340 km from the eye, which is well outside of convection of the TC core. The sounding from Patricia on 23 October had a mean $R^*$ of approximately one and a mean distance of approximately 11 km from the eye, which is well within eyewall convection.

The horizontal winds from the four equation sets agree well in both the NC and C soundings and show the same qualitative structure, with only slight differences between them (Fig. 3.16a, b). Figures 3.16c and 3.16d show the differences between the horizontal winds
from the three higher-order WFE methods (HF99, LM14a, and full WFE methodologies) and the xy-method. Both the NC and C soundings show that the largest differences are aloft, and the smallest differences occur in the low-levels. The C sounding, however, has the largest absolute differences (Fig. 3.16d). The direction of the difference (positive or negative) depends upon the method used, but the methods agree more within the NC sounding than the C sounding (Fig. 3.16c, d). This could be due to, in part, by the high amplitude noise in the differences in the C sounding (Fig. 3.16d).

Figure 3.19 shows notched box plots of the horizontal winds from each of the four methods. The edges of the notches denote the 95% confidence interval of the median. If the notches of any box plots overlap, then the medians are statistically similar (Chambers et al., 1983). The horizontal winds from the xy- and HF99 methods have medians that are statistically similar (Fig. 3.19). Only the full WFE and LM14a horizontal winds have statistically different medians (Fig. 3.19), but the difference in the medians are not physically large for any of the methods. Mean and median profiles of the horizontal wind speed at all radii illustrate that the largest variance between the four methods is above 12 km (Fig. 3.20). This agrees with the sample soundings in Figure 3.16. All four methods agree that the wind speed maximizes at 22 m s\(^{-1}\) at an altitude of 0.88 km.

### 3.2.3.1 Comparing to the xy-method

The mean, median, and standard deviation of the absolute difference between the three higher-order WFE horizontal winds and the xy-method horizontal winds is provided in Table 3.4. All three higher-order WFE methods have similar mean, median, and standard deviation absolute differences in the horizontal winds of approximately 0.6, 0.3, and 0.9 m s\(^{-1}\), respectively. Student’s t-tests show that the HF99, LM14a, full WFE methods have
statistically different horizontal winds compared to the xy-method at the 95% level. Only
the horizontal winds from the LM14a and full WFE methods are statistically different at the
99% level using Student’s t-tests. The results from Table 3.4 suggest that any of the higher-
order WFE methods offer statistically significant changes to the horizontal wind compared
to the xy-method.

Figure 3.21 shows histograms for the horizontal wind differences for all of the data. While all three higher-order WFEs have similar absolute horizontal wind differences and percent of difference to the xy-method horizontal wind, the HF99 method had a slightly negative skew and the full and LM14a methods had similar weak negative skews (Fig. 3.21a, b). All three methods have similar interquartile ranges (IQRs), with spans of approximately 0.65 m s$^{-1}$. Figure 3.21c indicates that using any of the three higher-order WFE equation sets produces approximately 4–8% change in the horizontal wind over the xy-method, which corresponds to approximately 0.5–1 m s$^{-1}$ (Fig. 3.21d).

The horizontal wind differences between the full WFE methodology and the xy-method horizontal winds are largest aloft and near the surface (Fig. 3.22a), which agrees well with the C sounding from Patricia (Fig. 3.16d). The differences also generally decrease in magnitude with increasing radius away from the TC cores. This indicates that the horizontal wind from soundings within the environments of the TCs are not as strongly affected by the method used as within the TC itself (Fig. 3.22b, c). It is also evident that the strength of $w$ impacts the strength of the difference, which is not surprising considering that $w$ is used in the full WFE method to obtain the horizontal wind (Fig. 3.22d). In areas where $w$ is weak or negative, larger differences between the xy-methodology and the full WFE methodology horizontal winds exist (Fig. 3.22d).

Figure 3.23 shows profiles of mean and median differences between the three higher-
order methods and the xy-method, as well as the standard deviations in the differences. Negative values indicate that the xy-method horizontal winds are weaker. The largest impact of the choice of method, and the overall variance in the wind speed differences, is largest aloft (Fig. 3.23). The differences are only statistically significant, however, above 12 km (Fig. 3.23a, b), which agrees with the findings in Figure 3.22a.

The general locations and conditions where the two methods differ (Fig. 3.22 and 3.23) suggests that using the full WFE method may impact the horizontal wind in key areas of the TCs and impact the interpretation of the strength of the horizontal wind physically. To test this hypothesis, the horizontal winds from the xy-methodology and the full WFE methodology were compared directly for transects of soundings across the TC centers. Figures 3.24a, b, 3.25a, b and 3.26a, b show the horizontal wind using the xy-method for select cross sections in Marty (27 September), Joaquin (2 October), and Patricia (23 October). These are the same cross sections analyzed in Section 3.1 (Figs. 3.12–3.14). The cross sections also show the change (Figs. 3.24b, 3.25b, 3.26b) or absolute change (Figs. 3.24a, 3.25a, 3.26a) in the horizontal wind by using the full WFE methodology in lieu of the xy-methodology.

The strongest location for absolute change in Marty occurs in sporadic pockets above 13 km (Fig. 3.24a). The largest absolute difference was approximately 6 m s\(^{-1}\) at 315 km from the eye and an altitude of 16.4 km (Fig. 3.24a), which is adjacent to a region of weak, positive vertical velocity (Fig. 3.12). The low-level (< 2 km) eyewall horizontal wind maximum is relatively unaffected by the use of the full WFE methodology (Fig. 3.24a, b). Most of the upper-level horizontal winds of Marty on 27 September are strengthened by 2–4 m s\(^{-1}\) by using the full WFE method, but there are areas aloft where the horizontal wind is weakened by −2 m s\(^{-1}\) (Fig. 3.24b).

Like in Marty, the largest absolute differences between the horizontal winds using the
xy-methodology and the full WFE methodology are aloft (Fig. 3.25a). However, absolute differences greater than 2–4 m s$^{-1}$ were observed at lower altitudes than in Marty, above 10 km (Fig. 3.25a). The largest absolute differences in Joaquin on 2 October were above 15 km in the downshear (southeast) side of the eyewall (Fig. 3.25a) above a strong updraft greater than 10 m s$^{-1}$ (Fig. 3.13). The horizontal winds using the full WFE methodology were generally faster aloft by 2–5 m s$^{-1}$, but one area aloft and adjacent to a weak updraft downshear to the southeast at 200 km was approximately 5 m s$^{-1}$ slower using the full WFE methodology (Fig. 3.25b).

The strongest location for absolute change occurs within the uppermost section of Patricia from 15–17.5 km (Fig. 3.26a). In some locations, the differences are large at 6 m s$^{-1}$ (Fig. 3.26a). Weaker, but notable 0.5–2 m s$^{-1}$ changes are within the eyewall (inner 20-40 km) and below the freezing level outside of the eyewall (below 6 km) (Fig. 3.26a). The midlevel, 5–6 km, horizontal wind maximum to the southeast side of the eye is strengthened by approximately 3 m s$^{-1}$ and broadened by using the full WFE methodology (Fig. 3.26a, b). Using the full WFEs increase the speed of the horizontal wind at the base of the TC outflow layer and increases the speed of the horizontal wind within the eyewall (Fig. 3.26b). Sporadic increases and decreases exist within the eye, and outside of the eyewall (Fig. 3.26b).

### 3.2.3.2 Comparing to the full WFEs

As all three higher-order methods produce statistically different horizontal winds to the xy-method, the full WFE method horizontal winds are compared directly to the HF99 and LM14a WFE method horizontal winds to examine the impact of using it over any of the other methods. The mean, median, and standard deviation of the absolute difference between the horizontal winds from the three other methods and the full WFE method is
provided in Table 3.5. The LM14a method and the xy-method have similar mean, median, and standard deviation absolute differences in horizontal wind to the full WFE method, but the HF99 methodology has much larger mean, median, and standard deviation absolute differences by approximately a factor of two (Table 3.5). Student’s t-tests also indicate that the full WFE method produces statistically different horizontal winds than any of the other methods at the 99% level.

The results in Table 3.5 are also supported by the histograms in Figure 3.27. The HF99 methodology has the largest spread in wind speed difference (Fig. 3.27a), largest absolute difference (Fig. 3.27b), largest percent differences (Fig. 3.27c), and smallest percentiles of absolute differences (Fig. 3.27d). The results in Figure 3.27 indicate that by using the full WFEs for the XDDs in TCI rather than the HF99 methodology, a 5–10% change or 1–3 m s$^{-1}$ difference in the horizontal wind can be achieved. The IQRs for the differences between the full WFE methodology and the xy-methodology or LM14a methodology horizontal winds are similar with spans of 0.5–0.6 m s$^{-1}$, but the IQR for the differences between the full WFE methodology and the HF99 methodology horizontal winds was statistically significantly larger at approximately 1.3 m s$^{-1}$.

Figure 3.28 shows profiles of mean and median horizontal wind speed differences between the full WFE method and the other methods. Negative values mean that the full WFE methodology produces weaker horizontal wind speeds. Like in Figure 3.23, the largest, statistically significant differences are above 12 km (Fig. 3.28). The HF99 and xy-methodologies have similar horizontal wind difference profiles (Fig. 3.28a, b), but the standard deviation in the horizontal wind speed differences between the HF99 and full WFE methodologies are considerably larger than for the xy- and LM14a methodologies (Fig. 3.28c). The LM14a methodology has a median difference of zero to the full WFE methodology horizontal winds.
below 13 km (Fig. 3.28a). The LM14a methodology also overestimates the horizontal wind speed aloft compared to the full WFE methodology (e.g., Fig. 3.28b).

Transect figures similar to Figures 3.24a, b, 3.25a, b, and 3.26a, b were produced comparing the HF99 methodology horizontal wind to the full WFE methodology horizontal wind (Figs. 3.24c, d, 3.25c, d, and 3.26c, d). Similar qualitative results can be obtained when comparing the two methodologies. One of the ubiquitous findings is that the absolute differences between the HF99 methodology and the full WFE methodology horizontal winds are larger than the absolute differences between the xy-method and the full WFE methodology horizontal winds, especially in the upper levels of all three cross sections (Figs. 3.24c, 3.25c, and 3.26c). This is similar to the findings in Table 3.5, implying that incorporating dropsonde accelerations without taking into account vertical velocity in the WFEs likely increases the dropsonde-derived horizontal wind errors. In many cases, the absolute differences exceed 5 m s\(^{-1}\), with pockets of greater than 6 m s\(^{-1}\) differences (e.g., Fig 3.26c). Given that the horizontal winds using the HF99 method are approximately 10 m s\(^{-1}\) in these areas aloft, percent differences can approach approximately 50%, which is both statistically and physically significant.

The largest differences occur: 1) in the upper levels of Marty (15–17.5 km), with radial bands below (Fig. 3.24c); 2) above 10 km on the downshear (SE) side of Joaquin (Fig. 3.25c); 3) above 10 km and outside of the inner 200 km on the upshear (NW) side of Joaquin (Fig. 3.25c); 4) in the upper levels of Patricia (15–17.5 km; Fig. 3.26c); 5) in the eyewall of Patricia, especially the upper and middle portions of the eyewall (Fig. 3.26c); and 6) areas below the freezing level outside of the eyewall in Joaquin and Patricia (Figs. 3.25c, 3.26c).

This means that the upper levels of all three TCs, especially for Patricia on 23 October, and the upper eyewalls, have horizontal winds that are stronger using the full WFEs rather
than the HF99 methodology (Figs. 3.24d, 3.25d, 3.26d). The full WFE method does produce weaker horizontal winds in some locations of the core, near the eye (e.g., Patricia; Fig. 3.26d), and upper levels at outer radii (e.g., Joaquin at 180 km southeast of the eye; Fig. 3.25d), but the overall impact of using the full WFEs is an increase of the horizontal wind in the upper levels of the cross sections by a mean of 0.75 m s\(^{-1}\) and a median of 0.5 m s\(^{-1}\).

### 3.2.4 Conclusions

The use of one of the three higher-order WFE sets (HF99, LM14a, or full) does change the horizontal wind in the TCI dataset using the XDDs. The difference is on the order of approximately 5% of the xy-methodology winds or approximately 0.5–1 m s\(^{-1}\) over the entire dataset (Fig. 3.21). This is close to the 0.5 m s\(^{-1}\) estimate by HF99, but specific areas of the TCs have larger changes of > 5 m s\(^{-1}\) (e.g., Fig. 3.25a).

The HF99, LM14a, and full WFE methodologies produced horizontal winds that were statistically different from the simplistic xy-methodology. Student’s t-tests show that all methods were statistically different from one-another, despite the medians being statistically similar for the xy- and HF99 methodology horizontal wind speeds (Fig. 3.19). The largest mean or median absolute difference in horizontal wind speeds, however, was between the HF99 methodology and the full WFE methodology (e.g., Tables 3.4, 3.5). The full WFE methodology is also the only methodology to include information on XDD accelerations and the vertical velocity. This suggests that the full WFE methodology is the most robust, physically correct, and complete methodology for the XDDs.

The full WFE method produces a 5–10% difference in horizontal wind, or approximately a 1–3 m s\(^{-1}\) difference compared to the HF99 methodology (Fig. 3.27). There are differences, however, of more than 5 m s\(^{-1}\) in key areas of the TCs such as the bottom of
the outflow layer, the eyewall, and potential rainband regions (Figs. 3.24, 3.25, 3.26). The HF99 method also underestimated the horizontal wind speed aloft to the full WFE method the most, with a mean and median of approximately $-0.75$ and $-0.54$ m s$^{-1}$, respectively.

The HF99 method horizontal winds also have the most spread and largest IQR for the differences from the full WFE method horizontal winds, whereas the LM14a method horizontal winds have the least spread and smallest IQR. Interestingly, the horizontal wind differences between the xy-method and the full WFE method horizontal are similar to the differences between the LM14a method and the full WFE method (Fig. 3.27). This collectively suggests that incorporating dropsonde fall speed and horizontal acceleration without accounting for vertical velocity or vertical acceleration like in the HF99 method erroneously increases the variance in the horizontal wind speed.

The largest impact of using the full WFEs is within the TCs themselves, rather than the environment, and in areas of weak or negative vertical velocity (Fig. 3.22). This is a result of equations 3.12 and 3.13, where only when $w = z$ does the horizontal wind equal the same as the xy-method. If $w \leq 0$, substantial differences in the horizontal winds speeds occur. This agrees well with the finding that the largest impacts occur within the upper levels of Marty and Patricia and below the freezing level outside of the eyewall region in Patricia. These situations, however, are in contrast to the large differences in the eyewall, especially the upper portions, where $w$ can be strongly positive and compete with $\dot{z}$, which would cause the horizontal winds from the full WFE method and the xy-method to be comparable. The large differences in the upper levels, especially the upper levels of the eyewall, likely occur due to the deceleration of the XDDs as they encounter strong updrafts. Strong deceleration would cause the denominators of equations 3.12 and 3.13 to be small, resulting in a larger difference.
The large, ±3–5 m s\(^{-1}\) differences aloft are not likely to be completely caused by the expected 2 m s\(^{-1}\) vertical velocity errors described in Section 2.4. By perturbing the observed vertical velocity by ±2 m s\(^{-1}\), horizontal wind errors associated with vertical velocity errors can be estimated. The horizontal wind errors caused by potential vertical velocity errors have an absolute mean and median between 0.25–0.57 m s\(^{-1}\) for the entire dataset. The absolute mean and median errors increase to approximately 0.57–1.54 m s\(^{-1}\) for data above 15 km, which does not fully account for the ±3–5 m s\(^{-1}\) differences aloft between the HF99 and full WFE methodologies.

The relatively small impact of the vertical velocity errors is because \((\ddot{z} - g) \gg (\dot{x})\) or \((\ddot{y})\) in Equations 3.12 and 3.13 for most of the XDDs launched into TCI. For example, the median horizontal errors aloft due to potential vertical velocity errors is only ±0.1 m s\(^{-1}\) in Patricia on 23 October, because the vertical deceleration of the XDDs as they encounter the convective eyewall and statically stable upper levels is exceedingly stronger than the horizontal acceleration of the dropsondes.

It is not shown here that the use of the full WFE method produces more accurate horizontal winds. There were no independent, collocated horizontal wind data in time and space to the TCI soundings to validate upon. Other flights either did not coincide with TCI soundings or they sampled other regions of the TCs. The results do show, however, that the use of a more complete, less approximated equation set yields statistically different horizontal winds, with a mean absolute change of at most 0.5–2 m s\(^{-1}\) over the entire dataset. This difference may be small and physically insignificant, but larger differences (> 5 m s\(^{-1}\)) were possible aloft are physically significant and warrant further examination of the equations used to derive horizontal wind from dropsondes.
Table 3.4: Mean, median, and standard deviation of the absolute differences between the HF99 methodology and xy-methodology horizontal winds in m s\(^{-1}\) (\(|V_2 - V_1|\), LM12a methodology and xy-methodology horizontal winds (\(|V_3 - V_1|\)), and full WFE methodology and xy-methodology horizontal winds (\(|V_4 - V_1|\)). Also included are the p-values from Student’s t-test between the methods compared. From Nelson and Harrison (2019).

|        | \(|V_2 - V_1|\) | \(|V_3 - V_1|\) | \(|V_4 - V_1|\) |
|--------|----------------|----------------|----------------|
| Mean   | 0.57           | 0.59           | 0.58           |
| Median | 0.32           | 0.33           | 0.32           |
| St. dev.| 0.87           | 0.93           | 0.90           |
| P-value| 0.02           | < 0.01         | < 0.01         |

Table 3.5: Mean, median, and standard deviation of the absolute differences between the HF99 methodology and full WFE methodology horizontal winds in m s\(^{-1}\) (\(|V_2 - V_4|\)), LM12a methodology and full WFE methodology horizontal winds (\(|V_3 - V_4|\)), and xy-methodology and full WFE methodology horizontal winds (\(|V_1 - V_4|\)). Also included are the p-values from Student’s t-test between the methods compared. From Nelson and Harrison (2019).

|        | \(|V_2 - V_4|\) | \(|V_3 - V_4|\) | \(|V_1 - V_4|\) |
|--------|----------------|----------------|----------------|
| Mean   | 1.10           | 0.61           | 0.58           |
| Median | 0.64           | 0.26           | 0.32           |
| St. dev.| 1.55           | 1.08           | 0.90           |
| P-value| < 0.01         | < 0.01         | < 0.01         |
Figure 3.16: Sample NC sounding from Marty on 27 September (a), and C sounding from Patricia on 23 October (b). The xy-methodology, HF99 methodology, LM12a methodology, and full WFE methodology horizontal winds in panels (a) and (b) are in black, red, blue, and green, respectively. The horizontal wind differences between methodologies for Marty (c) and for Patricia (d). The difference between the HF99 methodology and the xy-methodology horizontal winds is in red, the LM12a methodology and the xy-methodology horizontal winds is in blue, and the full WFE methodology and the xy-methodology horizontal winds is in green in panels (c) and (d). From Nelson and Harrison (2019).
Figure 3.17: Vertical velocity (m s$^{-1}$) from the Marty NC sounding on 27 September (blue) and the Patricia C sounding (red). From Nelson and Harrison (2019).
Figure 3.18: IR satellite image of Marty at 2045 UTC 27 September (a) and Patricia at 2045 UTC 23 October (b). Brightness temperatures (°C) are shaded. Sounding launch locations are shown as black diamonds. The sample soundings locations in Figures 3.16 and 3.17 are shown in white. IR image courtesy of David Vollaro. From Nelson and Harrison (2019).
Figure 3.19: Notched box plot comparisons between the horizontal wind speeds from V1, V2, V3, and V4. The inset to the bottom right shows that only the notches of the box plots for V1 and V2 overlap. From Nelson and Harrison (2019).
Figure 3.20: Median (a), mean (b), and standard deviation (c) profiles of V1, V2, V3, and V4 (black, red, blue, and green, respectively). From Nelson and Harrison (2019).
Figure 3.21: Comparison of the horizontal wind differences between the HF99 (blue), LM12a (red), and full WFE methods (green) to the xy-method. Panel (a) is a histogram of the wind speed differences. Panel (b) is a histogram of the absolute wind speed differences. Panel (c) is the percent difference histogram relative to the xy-method. Panel (d) is the percentiles of the absolute wind speed differences. The black solid lines in panel (d) denote the percentile for the 0.5 m s\(^{-1}\) absolute wind speed difference for the HF99 method difference. From Nelson and Harrison (2019).
Figure 3.22: Wind speed differences between the xy-methodology and the full WFE methodology with respect to altitude (a), distance from the TC center (b), $R^*$ (c), and vertical velocity (d). From Nelson and Harrison (2019).
Figure 3.23: Median (a), mean (a), and standard deviation (c) profiles of wind speed differences for $|V_2 - V_1|$ (blue), $|V_3 - V_1|$ (red), $|V_4 - V_1|$ (green). Differences that are statistically different at the 95% level using Student’s t-test are denoted with dots. From Nelson and Harrison (2019).
Figure 3.24: Cross section of horizontal wind from Marty on 27 September. Shown in solid black contours are the horizontal winds using the xy-methodology (a, b) or the HF99 methodology (c, d). Absolute differences to the full WFE methodology horizontal winds are shown in panels (a) and (c) and differences to the full WFE methodology horizontal winds are shown in panels (b) and (d). The TC center is denoted with a thick solid black line. From Nelson and Harrison (2019).
Figure 3.25: Same as Fig. 3.24, but for Joaquin on 2 October. From Nelson and Harrison (2019).
Figure 3.26: Same as Fig. 3.24, but for Patricia on 23 October. From Nelson and Harrison (2019).
Figure 3.27: Same as Fig. 3.20, but for wind differences between the HF99 (blue), LM12a (red), and xy-methods (green) to the full WFE method. From Nelson and Harrison (2019).
Figure 3.28: Same as Fig. 3.23, but for wind speed differences for $|V_1 - V_4|$ (green), $|V_2 - V_4|$ (blue), $|V_3 - V_4|$ (red). From Nelson and Harrison (2019).
3.3 Temporal and spatial autocorrelations: Implications for future dropsonde-based missions

3.3.1 Introduction

Due to the high sampling rate of the XDDs, it is possible that successive data points in a sounding, or data points from adjacent soundings, were appreciably correlated (i.e., correlation values greater than 0.5; Brooks and Carruthers, 1978), and likely represented the same atmospheric phenomena, such as an updraft or small-scale vorticity maximum. Until recently (Nelson et al., 2019b), no study has considered the temporal and spatial autocorrelations (the correlation between nearby data points with respect to time or space; Brett and Tuller, 1991; Griffith, 2003; Khalili et al., 2007) of dropsondes in TCs. Only one study, Black et al. (1996), has examined the spatial autocorrelations of radar data in TCs. Analysis of the temporal and spatial autocorrelations of the TCI soundings are important to: 1) aid targeted dropsonde or dropsonde deniability studies; 2) evaluate what features are resolvable by the dropsondes; 3) performing accurate spatial interpolation of any recorded variable; and 4) estimate the required horizontal spacing of dropsondes in TCs in future campaigns. This dissertation only focuses on the latter four points.

Knowledge of the temporal and spatial autocorrelations of dropsondes is also required in order to accurately resolve TC structure. Some studies indicate that to resolve features on the scale of the radius of maximum wind (RMW), grid spacing of approximately 14 km or less is required (Gentry and Lackmann, 2010). The results of Gentry and Lackmann (2010), however, show that increased model resolution down to 2-km grid spacing or less is required to understand TC eyewall kinematics and physics. These results suggest that observations should also be taken at high-resolutions. The likelihood of highly correlated data points
increases, however, with the increase in horizontal or vertical resolution and should approach unity (Brett and Tuller, 1991; Khalili et al., 2007). Conversely, if dropsondes are launched too far apart then the thermodynamic and kinematic structure of a TC will not be well resolved or represented. Similarly, if data in a single sounding is recorded at low frequency, the thermodynamic and kinematic structure of a TC will not be well resolved or represented.

Examination of the temporal and spatial autocorrelations in the XDDs is critical to accurately perform any objective spatial interpolation. Temporal and spatial interpolation can be conducted linearly or with higher-order, more complex schemes (Gorman, 2009; Privé and Errico, 2016). If adjacent data points in space or time are appreciably correlated, well modeled, or vary slowly in time and space, interpolation can easily be conducted between the data points (Gorman, 2009). If adjacent data points are not appreciably correlated, however, then interpolation cannot be as easily conducted. The choice of a coarse, low-correlation interpolation scheme could create unrealistic and uncharacteristic TCs by smoothing or smearing small-scale phenomena or sharp gradients in time and space (Privé and Errico, 2016). In such situations, more complex interpolation schemes would need to be employed.

One interpolation scheme, called kriging, is a geostatistical interpolation method that uses covariance information in the data to interpolate data fields (e.g., Biau et al., 1999). Like other interpolation schemes, the success of kriging hinges upon accurately predicting the value of a data point from neighboring data points. If data are highly uncorrelated or have an abnormally high covariance, then the ability to successfully apply kriging suffers. One of the important distinctions between statistical interpolation methods like kriging and observational data assimilation methods (discussed previously) is that kriging is based completely on observations (Biau et al., 1999). Data assimilation is based upon observations, model physics, resolution, and domain size (e.g., Aberson, 2008). Successful kriging of data
to uniform grid spacing can also be used to validate models at a resolution different than that of the observations.

Temporal and spatial (both horizontal and vertical) variability of observations in various atmospheric phenomena suggest a complex relationship between the autocorrelation, observational density, observation method, and location of the observations. Tables 3.6 and 3.7 summarizes the findings of studies that examined the temporal or spatial autocorrelations for horizontal wind speed (referred to as $|V_h|$ in this section), (referred to as $T$ in this section), water vapor, precipitation, and vertical velocity (referred to as $w$ in this section). There are large variations in the autocorrelation horizontal distances in the variables considered in Tables 3.6 and 3.7, with lengths ranging from 200 m ($w$; Lothon et al., 2006) to 1000 km ($T$; Gunst, 1995). The vertical autocorrelation length scales for $w$ and water vapor given in Tables 3.6 and 3.7 are comparable, and less than 1 km (Fisher et al., 2013; Lothon et al., 2006). The 0.5-autocorrelation temporal scales for $T$ and horizontal wind speed (Tables 3.6 and 3.7) are comparable and are between 4–12 h and are a function of altitude (Brett and Tuller, 1991; Raymond et al., 2003; Pérez et al., 2004). Horizontal autocorrelation spatial scales for $T$ are greater than, or are comparable to, the horizontal autocorrelation spatial scales for horizontal wind (Tables 3.6 and 3.7).

Convection, and variables related to convection (e.g., precipitation rates), should have smaller correlation length scales horizontally due to higher small-scale variance (Fisher et al., 2013). Spatial autocorrelations in precipitation and rain rate drop below 0.5 from 1.5 to 10 km, with convective precipitation primarily at 4 km and stratiform precipitation primarily at larger distances (Tables 3.6 and 3.7). Lothon et al. (2006) examined the autocorrelation of $w$ in the daytime, convective, planetary boundary layer (PBL) using Doppler Lidar data and found small, 0.5, autocorrelation distances between 200–300 m both horizontally...
and vertically (Tables 3.6 and 3.7). Black et al. (1996) found that $w$ autocorrelations of approximately 0.2 were statistically significant, horizontal and vertical autocorrelation distances were between 1–6 km, and updrafts were more spatially correlated than downdrafts, especially within the eyewall. The 0.2-autocorrelation threshold noted in Black et al. (1996) indicates statistically significant relationships, but does not indicate that the autocorrelation is strong. The use of a higher autocorrelation threshold, like 0.5, would indicate a stronger relationship and decrease the horizontal, and vertical, autocorrelation distances in Black et al. (1996) by approximately 50%.

The definition of convection, updrafts, and downdrafts is also important in discerning the autocorrelation scales within those updrafts and downdrafts. Jorgensen et al. (1985) defined convective vertical motions in TC flight-level data as continuous positive or negative vertical velocities for at least 500 m, with at least one data point achieving a magnitude of 0.5 m s$^{-1}$. Convective cores were defined as continuous $w$ magnitudes of at least 1 m s$^{-1}$ for 500 m or greater. These distances and values were determined iteratively and subjectively in LeMone and Zipser (1980). This definition was also adopted by studies such as Black et al. (1994); however, the spatial correlations of the $w$ data were not presented. Black et al. (1996) defined an updraft or downdraft using the larger $|1.5 \text{ m s}^{-1}|$ and $|3 \text{ m s}^{-1}|$ thresholds.

An analysis was conducted to evaluate the temporal and spatial autocorrelations of the XDDs used in TCI with the kriging spatial interpolation framework. The autocorrelation of data points in individual soundings as well as the spatial correlation between adjacent soundings were considered. Autocorrelation distances and times below the spatial and temporal resolution of the dataset are interpolated estimates limited by the spacing and number of observations. The minimum, maximum, mean, and median sounding spacing for each day is provided in Table 3.8 for reference.
3.3.2 Data and methods

The temporal and spatial autocorrelations were computed for $w$, $|V_h|$, $T$, potential temperature ($\theta$), and $RH$. Adjacent data points in time and space with correlations above 0.5 are considered highly correlated (Brooks and Carruthers, 1978). The 0.5-autocorrelation threshold is statistically significant well above the 95% confidence level in both time and space for all variables in the dataset (not shown). The vertical velocities, TC centers, and RMWs were obtained following the methodology in Sections 3.1 and 3.2. The data restrictions were the same as in Section 3.1, which leaves a total of 437 dropsondes (276,659 data points).

To calculate autocorrelations of adjacent dropsondes at a fixed altitude (dropsonde-to-dropsonde), data points were examined every kilometer from 0 to 17 km. A buffer of $\pm 0.125$ km for each altitude was included because the likelihood that all 437 dropsondes reported at exactly the same altitude is very low. For example, only 27 data points out of the entire dataset reported at exactly 2 km. The size of the buffer zone was chosen to match the altitudinal binning scheme in Section 3.1 for the CFADs. Spatial autocorrelations were computed using the “correlog” function in the R software package. The correlog function measures spatial dependence using Moran’s $I$, which can be simplified following Bjørnstad and Falck (2001) to be:

$$\bar{r}_t(k, m) = \frac{1}{m} \sum_{i=1}^{m} r_t$$

where the autocorrelation ($\bar{r}_t$) is calculated over a distance class ($k$) for the length of data within each distance class ($m$). (Note: The notation used here is different than what is provided in Bjørnstad and Falck (2001)). Distance class increments of 5 km were used for all dates and all TCs, except for Patricia on 20 October. A distance class increment of 10
km was used for Patricia on 20 October because of the large spacing between soundings. Increment classes that are too small compared to the horizontal resolution of the soundings causes unrealistic and noisy autocorrelations with values above one.

To calculate the autocorrelations within an individual sounding, data were ordered with respect to time and the “acf” function in the R software package was used. This was done for each observation day and for each storm. The acf function computed autocorrelation using the following equations:

\[ r_t = \frac{c_t}{c_o} \]  

\[ c_t = \frac{1}{n} \sum_{\min(n-t,n)}^{\max(1,t)} (X_{s+t} - \bar{X})(X_s - \bar{X}) \]  

\[ c_o = \frac{1}{n} \sum (X - \bar{X})^2 \]

where \( r_t \) is the autocorrelation, \( c_t \) is the autocovariance, \( c_o \) is the variance of the series, \( n \) is the length of the series, \( X \) is the value in the series, \( \bar{X} \) is the mean of the series, \( t \) is time, and \( s \) is some lag forward in time (Venables and Ripley, 2002).

In order to compute the temporal and spatial autocorrelation scales, the data within any sounding need to be detrended (Janert, 2011). If a trend or mean state is present in the data, then correlograms show smoothed and high-amplitude periodic curves or large, negative correlations at long lags (see Appendix). Rather than using a linear detrend, median atmospheric profiles of \( w \), \( T \), \(|V_h|\), \( RH \), and \( \theta \) were used to detrend the data.

Six detrend methods were explored: 1) no detrend; 2) detrend using median profiles
from a specific date (date detrend); 3) detrend using median profiles from a specific TC (storm detrend); 4) detrend using median profiles from the entire dataset (total detrend); 5) detrend using median profiles within four radial sections from the entire dataset (radial detrend); and 6) detrend using median profiles within four radial sections from a specific date (D+R detrend). The four radial sections were: 1) \( \leq 1.25R^* \); 2) 1.25–3R*; 3) 3–5R*; and 4) 5–10R*. The 1.25R* radius was chosen because DeHart et al. (2014) found that the highest frequencies of updrafts and downdrafts in the core occurred between 0.75R* and 1.25R*. 3R* was also chosen to reflect the outermost of the core (Rogers et al., 2013), and 5R* was chosen because it is the midpoint of the R* values. Beyond 5R*, composite low-level azimuthal winds decreased substantially in strength (not shown).

The six methods are presented and compared in the Appendix. All spatial 0.5-autocorrelation scales were statistically similar, except for the D+R detrend \( T \) and \( \theta \) data. The D+R detrended temporal 0.5-autocorrelation thresholds were also statistically different from the other detrending methods in most cases. The 0.5-autocorrelation temporal thresholds without detrending were significantly larger for all variables, except \( w \). The statistically larger temporal autocorrelations for the no detrend data are due to the presence of a mean state that varies with altitude and should not be used. The sixth method (D+R detrend) was ultimately used, because it accounted for the variance in the mean state radially, from date-to-date, and from storm-to-storm.

The D+R detrend median profiles for each variable and each date are provided in Figures 3.29–3.34 and the total number of soundings in each radial section are provided in Table 3.9. The mean and median number of soundings in each radial section was 11–12, with a maximum of 24 (Joaquin on 5 October) and a minimum of two (Patricia on 20 October) soundings. Many of the median \( w \) profiles resemble profiles observed by Black
et al. (1996) and primarily show weak subsidence or weak positive vertical motions below
the average freezing level (5–6 km) and strong positive vertical velocities aloft (Figs. 3.29,
3.31, 3.33). The $w$ median profiles were especially noisy, however, in Patricia on 20 October
and 23 October likely due to the low number of soundings in the radial section (Table 3.9) or
strong vertical motions in the eyewall (e.g., Fig. 3.14). The $|V_h|$ median profiles differ from
day-to-day and show the evolution of the TC wind fields in each TC, but also show that
peak $|V_h|$ strengths generally occurred between 0.5 and 1 km (Figs. 3.29, 3.31, 3.33). The
$|V_h|$ median profile for Patricia on 23 October had a noisy double jet structure, with strong
median $|V_h|$ from 5–7 km similar to the double jet structure in the eyewall of Patricia shown
by Rogers et al. (2017) (Fig. 3.33e). Median $RH$ profiles show that the lowest 6 km were
fairly moist and varied slightly from day-to-day, but the upper levels were dry (Figs. 3.29,
3.31, 3.33). The zero percent RH values above 12.5 km are a manifestation of the sensor
performance below $-40^\circ$C (e.g., Bell et al., 2016). $T$ and $\theta$ varied slightly from day to day
and had smooth decreases aloft for $T$ and increases aloft for $\theta$ (Figs. 3.30, 3.32, 3.34).

3.3.3 Results

The autocorrelations for each TC and in total were plotted as correlograms. Individual
correlograms for each of the ten days in the dataset are not provided, but the results from
those figures are summarized in Tables 3.10 and 3.11 and Figure 3.35. Correlograms for
each TC are provided in Figures 3.36–3.38. The correlograms are smoothed splines fitted to
scatterplots of the correlograms for each sounding or altitude level. Table 3.10 documents
the autocorrelation spatial scales where correlation drops below 0.5 for adjacent data points
at a fixed altitude (dropsonde-to-dropsonde). Table 3.11 documents the autocorrelation time
scales where correlation drops below 0.5 for data within a given individual sounding. The
means, medians, and standard deviations are included in Tables 3.10 and 3.11.

### 3.3.3.1 Correlations from dropsonde-to-dropsonde

RH and w had the smallest mean and median spatial autocorrelation length scales at 4–5 km as well as the smallest spreads and standard deviations (Table 3.10). T, |V_h|, and θ had much larger spreads in spatial autocorrelation thresholds. Mean and median T and θ spatial autocorrelation length scales were 5–7 km, but mean and median |V_h| spatial autocorrelation length scales were 9–11 km. Most of the autocorrelation length scales were comparable in magnitude or less than the minimum sounding spacing on each day (Table 3.8).

The autocorrelation length scales for all variables increased with increasing RMW (Fig. 3.35a). w, RH, and T had the strongest positive correlations with RMW size. The relationship between the variables and the RMW is consistent with the well-recognized idea that gradient or thermal wind balance dominates the storm-scale structure of TCs (e.g., Willoughby, 1990; Molinari et al., 1993). Figure 3.35a also illustrates that most of the autocorrelation length scales are smaller than the RMW by a factor of 4–8, with w mostly on the low-end and |V_h| on the high-end of the range. Despite the relationship between the RMW and the autocorrelation length scales, data are still grouped by each TC to examine the differences in the temporal and spatial autocorrelations present from storm-to-storm.

Figure 3.36a shows the spatial correlograms for all five variables in Marty. The autocorrelations decrease dramatically within 25 km and fluctuate around zero thereafter (Fig. 3.36a). w and T had the lowest acceptable spatial correlation length scales at 2.8 km (Fig. 3.36a). RH and θ had acceptable spatial autocorrelations between 3–4 km (Fig. 3.36a). |V_h| had the highest spatial autocorrelation threshold at 4.4 km (Fig. 3.36a).
While \( RH \) for Joaquin was highly correlated within approximately 3.5 km like Marty (Fig. 3.37a), autocorrelation distances were larger for the other variables considered. \( w \) had an autocorrelation length scale of approximately 3.5 km, and \( T \) and \( \theta \) had autocorrelation distances between 5–6 km (Fig. 3.37a). \( |V_h| \) had the largest autocorrelation distance threshold at approximately 11.5 km (Fig. 3.37a). All of the variables decrease in correlation quickly within 25 km and fluctuate around zero, but the \( |V_h| \) correlogram shows negative correlations for distances between 25–50 km (Fig. 3.37a). The peak negative correlations for \( |V_h| \) occurred at a distance equivalent to the average RMW size in Joaquin.

The acceptable spatial autocorrelation thresholds in Patricia were smaller than in Marty or Joaquin for all variables (Fig. 3.38a). \( w, RH, T, \) and \( \theta \) all had autocorrelation distance scales at approximately 2 km. \( RH \) and \( |V_h| \) had slightly larger autocorrelation distance scales at approximately 3 km. The correlograms for \( T \) and \( \theta \) in Patricia had a negative peak at approximately 15 km, similar to \( |V_h| \) in Joaquin, but weaker (Fig. 3.38a). \( |V_h| \) had a positive peak at 20 km Fig. 3.38a). At distances longer than 25 km, autocorrelations fluctuated around zero Fig. 3.38a).

Figures 3.36b, 3.37b, 3.38b show the 0.5-autocorrelations with respect to altitude. The 0.5-autocorrelation horizontal length scales for Marty, Joaquin, and Patricia were non-linear functions of altitude (Figs. 3.36b, 3.37b, 3.38b), but consistent patterns from storm-to-storm did not exist. The \( w, RH, T, \) and \( \theta \) 0.5-autocorrelation horizontal length scales in Marty decreased to some degree with increasing altitude, but \( |V_h| \) had peaks at 9 km and in the lowest few 100 m (Fig. 3.36b). Joaquin had more complex altitudinal relationships, where \( RH \) temporal autocorrelation thresholds increased slightly with increasing altitude, \( |V_h| \) temporal autocorrelation thresholds decreased slightly with increasing altitude, and \( w, T, \) and \( \theta \) had various large peaks in autocorrelation threshold at different altitudes (Fig. 3.37b). In
Patricia, the $|V_h|$ temporal autocorrelation thresholds increased with height, $T$ and $\theta$ temporal autocorrelation thresholds decreased slightly with height, $RH$ temporal autocorrelation thresholds were close to constant at all altitudes, and $w$ temporal autocorrelation thresholds peaked at 6 km (Fig. 3.38b).

To put the autocorrelation length scales into context, the values are compared to the correlation length scales in Table 3.6 and 3.7. The correlation distances observed in non-TC studies, except for $w$, are considerably large compared to what was observed in the TCI data. For example, the 0.5-autocorrelation lengths for $T$ observed on an individual day and in an individual TC are much smaller than the horizontal autocorrelation distances observed by Gunst (1995) and Nichol and Wong (2008) for $T$. The autocorrelation length scales for $w$ were primarily between 2 and 6 km from day-to-day and 2 and 4 km from storm-to-storm (Table 3.10 and Figs. 3.36a, 3.37a, 3.38a). The $w$ length scales are most comparable to the rainfall and convective rain rate autocorrelation distances over land with rain gauge and radar data in Habib et al. (2001), Bringi et al. (2015), and Jameson (2017). They are also slightly smaller than the $w$ 0.2-autocorrelation length scales adjacent to updrafts and downdrafts in TCs as shown by Black et al. (1996) but are comparable if Black et al. (1996) used a 0.5-autocorrelation threshold. Most of the $w$ autocorrelation length scales observed in the TCI data are a factor of ten larger than the 0.5-autocorrelation horizontal length scale observed with Lidar data over land by Lothon et al. (2006).

3.3.3.2 Correlations within a sounding

The acceptable temporal autocorrelation scales were above 8 s for all variables and for each observation day, with most above 15 s (Table 3.11). Mean and median temporal autocorrelation scales ranged from 17.5–31 s for all variables (Table 3.11). The smallest
mean and median temporal scales were for \( w, T, \) and \( \theta \). The smaller temporal autocorrelation thresholds in \( T, \theta, \) and \( w \) could be due to smaller thermal perturbations away from the median profiles in each radial section (e.g., Fig. 3.32) and weaker vertical motions dominating the vertical velocity distribution (e.g., Fig. 3.11). Figure 3.35b shows that as the horizontal autocorrelation length scale increases, so does the temporal autocorrelation for all variables, except \( w \). This is not surprising, but could be due to either a positive relationship between the vertical and horizontal scales of the variables considered or horizontal drift of the dropsonde during descent. The strong, negative correlation between the temporal and spatial autocorrelations for \( w \) is caused by one spatial autocorrelation threshold outlier in Patricia on 20 October, where few dropsondes were launched (Table 3.9). If this data point was removed, the correlation would be positive at 0.26. The estimated still air dropsonde fall speed ranges from approximately 52 m s\(^{-1}\) aloft to 18 m s\(^{-1}\) at sea-level. It is estimated from the typical fall speeds that vertical autocorrelation length scales would likely range from 0.1–2 km.

The temporal autocorrelations were between 17–28 s for all variables in Marty, with \( \theta \) and \( w \) at the shortest 0.5-autocorrelation time scales of 17 and 21 s, respectively (Fig. 3.36c). \(|V_h|\) and \( RH \) had comparable 0.5-autocorrelation time scales of 28 s (Fig. 3.36c). All variables in Marty decreased in autocorrelation quickly within 60 seconds and intercepted the zero-autocorrelation line within 100–120 s (Fig. 3.36c). Weak, negative autocorrelation values were observed at longer time lags (Fig. 3.36c).

Joaquin had the longest 0.5-autocorrelation time scales for all variables and ranged from 22–34 s (Fig. 3.37c). Like in Marty, \( \theta \) and \( w \) at the shortest autocorrelation time scales of approximately 22 s, and \(|V_h|\) and \( RH \) had the largest time scales at 34 s (Fig. 3.37c). \( T \) had an autocorrelation time scale comparable to \( w \) and \( \theta \) at 25 s (Fig. 3.37c). The temporal
autocorrelations in Joaquin also decreased to zero within 100–120 s and remained weakly negative (Fig. 3.37c).

Patricia had comparable temporal autocorrelation scales to Marty ranging from 12–29 s (Fig. 3.38c). The decrease in autocorrelation within 60 s was sharper in Patricia than in Marty or Joaquin for $w$, $T$, and $\theta$, leading to short autocorrelation temporal scales from 12–20 s (Fig. 3.38c). The autocorrelations, however, still decreased to zero within 100–120 s and remained weakly negative afterward (Fig. 3.38c). Like Marty and Joaquin, $|V_h|$ and $RH$ had the largest time scales at 27 and 29 s, respectively (Fig. 3.38c).

The 0.5-autocorrelation temporal scales for Marty, Joaquin, and Patricia were also non-linear functions of radius (Figs. 3.36d, 3.37d, 3.38d). Figures 3.36d, 3.37d, 3.38d show the smoothed 0.5-autocorrelations with respect to the mean radius of the sounding. The 0.5-autocorrelation temporal scales decreased with radius or remained constant within the inner 150 km in Marty but increased outside of 150 km (Fig. 3.36d). $|V_h|$, $T$, and $\theta$ 0.5-autocorrelation temporal scales sharply decreased within the inner 50–100 km of Joaquin (Fig. 3.37d) and slowly decreased outside of 100 km, but $|V_h|$ had high amplitude oscillations at larger radii. $w$ and $RH$ increased slightly with increasing radius with some oscillations (Fig. 3.37d). The 0.5-autocorrelation temporal scales in Patricia, except $RH$, generally decreased with increasing radius (Fig. 3.38d). The 0.5-autocorrelation temporal scales for $RH$ in Patricia increased gradually within 150 km and decreased outside of 150 km (Fig. 3.38d).

### 3.3.3.3 Correlations within updrafts and downdrafts

Given that the typical structure of a TC features strong kinematic and thermal perturbations within the convective eyewall and rainbands, it is possible that the 0.5-autocorrelation...
temporal scales differ in soundings that observed updrafts or downdrafts from soundings in less convective areas. It is also possible that the temporal scales in these updraft and downdraft soundings differ from the findings in Figures 3.36–3.38 and Table 3.11, which include all soundings in the dataset. Updrafts and downdrafts are defined using the methodology in Section 3.1.

As an example, shown in Figures 3.39 and 3.40 are sounding profiles from the convective eyewall of Patricia on 23 October. The red lines denote the start and end of the updraft. The updraft occurred in the midlevels, was 7.45 km deep, and persisted for over 400 s (Figs. 3.39, 3.40). The updraft was also collocated with the midlevel jet shown by Rogers et al. (2017), high-\(RH\) values, and small variations in \(T\) and \(\theta\). These perturbations were also evident after subtracting out the median state over the same depth and time scale (Fig. 3.41). The temporal autocorrelations within this sounding were significantly larger than for the entire date, with a p-value of 0.003 (Fig. 3.42). The autocorrelations for the Patricia eyewall sounding ranged from 43 s (\(RH\)) to 107 s (\(|V_h|\)).

Temporal autocorrelations were computed for all 78 updraft and 37 downdraft soundings on each day and are provided in Tables 3.12 and 3.13. The number of updraft and downdraft soundings for each day is provided in Table 3.14. The mean and median \(w\), \(|V_h|\), \(T\), and \(\theta\) 0.5-autocorrelation temporal scales in updraft soundings were larger than for the temporal scales in all soundings, but the differences were not statistically significant by Student’s t-tests (Tables 3.11, 3.12). The mean and median 0.5-autocorrelation temporal scales for \(RH\) in updraft soundings were smaller and statistically significant (Tables 3.11, 3.12). Only \(w\), \(T\), and \(\theta\) had larger mean and median temporal scales in downdraft soundings (Tables 3.11, 3.13), but none of the differences between downdraft soundings and all soundings were statistically significant.
Figures 3.43 and 3.44 show the temporal autocorrelations for individual soundings computed similar to the single sounding in Figure 3.42. The temporal scales for \( w \), \(|V_h|\), \( T \), and \( \theta \) in updraft soundings have positive correlations with the maximum updraft depth in the soundings (Fig. 3.43). The correlation for \( w \) was exceptionally strong at 0.76 and a p-value well below 0.05 (Fig. 3.43a). Correlations were also statistically significant at a p-value below 0.05 for \(|V_h|\) and \( \theta \). \( RH \) featured a weak, negative correlation in updraft soundings (Fig. 3.43c). In opposition to the updraft soundings, the downdraft soundings had near-zero or weakly negative correlations between the maximum downdraft depth and temporal autocorrelation scale, with no statistically significant relationships (Fig. 3.44). The positive correlations for updraft soundings indicate that there are statistically significant relationships between the temporal autocorrelation scales and the depth of the updrafts even though the mean and median temporal autocorrelation scales do not differ from the total dataset.

3.3.4 Discussion

From the large dataset of 437 XDDs in three TCs, it was evident that temporal autocorrelations for any given dropsonde were approximately 20 s for \( w \), \( T \), and \( \theta \), and 30 s for \(|V_h|\) and \( RH \) in the entire dataset. This corresponds to an approximate altitudinal depth of 0.3–1 km and 0.5–1.5 km, respectively, given the typical XDD fall speeds. The temporal autocorrelations scales suggest that interpolating sounding data to matching altitudes is justifiable within small 0.5-km intervals. This also implies that the XDD sampling frequency adeptly oversampled the TCs in TCI.

The 0.5-autocorrelation temporal scales were both a function of radius and depth/strength of vertical motion. The temporal scales decreased within 100 km by 10–20 s for most variables in Marty, Joaquin, and Patricia. The exception was \( RH \) in Joaquin and Patricia,
which increased within 100 km. Consistent patterns outside of 100 km were not present in the dataset. This agrees well with the finding that there were positive correlations between updraft depth and temporal autocorrelation scale, as $u$ was strongest within the inner cores of the three TCs (e.g., Fig. 3.9d).

From dropsonde-to-dropsonde, one of the conclusions that can be drawn is the minimum spatial distribution of dropsondes needed to accurately depict a TC from the observed atmospheric variables. Another way to phrase the previous statement is: “How close together can the XDDs be in TCs before adjacent data points become appreciably correlated?” The horizontal autocorrelation length scales for all variables, except for $w$ (Black et al., 1996; Lothon et al., 2006), are smaller than what was observed in previous studies (Tables 3.6 and 3.7). Specifically, $|V_h|$ (Wylie et al., 1985) and $T$ (Gunst, 1995; Nichol and Wong, 2008) autocorrelation length scales are smaller for all observation days in the dataset. It is important to note that one cannot truly know the spatial correlation limit without testing observations (like the XDDs) at a much higher launch rate/smaller horizontal resolution. The autocorrelations below the minimum horizontal sounding spacing (e.g., Patricia on 23 October; Tables 3.8, 3.10) are estimates that are limited by the spacing of the original dataset. The relatively high resolution of the original dataset could be why some of the autocorrelation length scales for the TCI data are smaller relative to past studies (Tables 3.6 and 3.7). It is also plausible that the features measured by the non-TC studies were synoptic-scale features rather than mesoscale features like in the three TCs observed during TCI, which would lead to smaller autocorrelation length scales (Tables 3.6 and 3.7). Regardless, the agreement between the spatial autocorrelations for $w$ in this study and the spatial autocorrelations for $w$ radar data adjacent to updrafts and downdrafts in Black et al. (1996) is encouraging and provides support for the findings herein.
The medians for all of the individual days illustrate that $w$, $RH$, $T$, and $\theta$ all had low spatial autocorrelations between 4–6 km (Table 3.10). This agrees well with the model grid spacing required to resolve TC eyewall kinematics and physics (Gentry and Lackmann, 2010). $|V_h|$ had a slightly larger dropsonde-to-dropsonde spatial autocorrelation scale with a median of approximately 10 km, which agrees well with the model grid spacing required to resolve features on the scale of the average RMW (approximately 55 km) found by Gentry and Lackmann (2010). When data were combined for each TC, $w$ always had the smallest autocorrelation length scale, with the mean and median below 3 km. $|V_h|$ always had the largest autocorrelation length scale between 3–12 km. Spatial correlations for $RH$, $T$, and $\theta$ were between 2–6 km.

The spatial requirements for the XDDs for each atmospheric variable present an operational challenge for future TC dropsonde campaigns. The spatial autocorrelations presented in this study suggest that the smallest spatial resolution (approximately 3–4 km) and quickest launch frequency was at the limit of the required spatial resolution needed to accurately depict TC structure. In situations where the spatial resolution was larger than 3–4 km, spatial interpolation cannot be accurately conducted and does not accurately depict the thermal or kinematic structure of these three TCs. The same conclusion can be made if dropsondes are launched at a resolution of 3–4 km, but one dropsonde fails. The latter situation suggests that a smaller horizontal spatial resolution of soundings than what was achieved during TCI should be used in future dropsonde-based TC campaigns to accurately depict the kinematic, moisture, and thermal fields. The results also imply that the launch rate needs to be increased by a factor of four to fully resolve convection and thermal perturbations in TCs, except for possible small-scale (smaller than 3 km) eyewall vorticies (Grasso, 2000; Gentry and Lackmann, 2010). This assumes that the XDDs can adequately measure both weak and
strong convection, since the expected errors are $\pm1$–$2$ m s$^{-1}$.

The $w$, $RH$, $|V_h|$, $T$ and $\theta$ horizontal autocorrelation scales found in the three TCs observed during TCI are considerably smaller than the typical length scales of background errors in models (Andersson et al., 1993; Irvine et al., 2011; Rizvi et al., 2012; Wang et al., 2014). Based upon Liu and Rabier (2002) and Gentry and Lackmann (2010), if a model with 2-km grid spacing and a domain size of 1000 km (order of magnitude of the diameter of the TCs observed in TCI) was used and 50 XDDs were assimilated at one time (approximate number of XDDs launched each day during TCI), then the spacing of the XDDs would need to be 20 km apart. The hypothetical distance of 20 km is larger than the daily autocorrelation length scales for all variables examined by at least a factor of two.
Table 3.6: Summary list of spatial (horizontal and vertical) and temporal autocorrelation scales referenced in the text based upon correlation thresholds of either 0.5 or 0.37 for horizontal wind ($|V_h|$), temperature ($T$), water vapor, rainfall, rain rate, and vertical velocity ($w$). Correlation length scales that were specifically for convective regions are denoted as “C” and non-convective regions are denoted as “NC”. Observation types (obs. type) are listed and the locations of the observations are noted for each referenced study. Observation types include: surface (Sfc. stations), boat (boat stations), radio acoustic sounding system (RASS), satellite, lidar, S-band radar, or X-band radar. From Nelson et al. (2019b).

<table>
<thead>
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<tbody>
<tr>
<td>$</td>
<td>V_h</td>
<td>$</td>
<td>0.5</td>
<td>——</td>
<td>0–100 km</td>
<td>——</td>
<td>Sfc. stations</td>
</tr>
<tr>
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<td>$</td>
<td>0.5</td>
<td>——</td>
<td>400 km</td>
<td>——</td>
<td>Boat stations</td>
</tr>
<tr>
<td>$</td>
<td>V_h</td>
<td>$</td>
<td>0.5</td>
<td>——</td>
<td>——</td>
<td>4–6 h</td>
<td>Sfc. stations</td>
</tr>
<tr>
<td>$</td>
<td>V_h</td>
<td>$</td>
<td>0.37</td>
<td>——</td>
<td>——</td>
<td>11 h (at 40 m)</td>
<td>RASS</td>
</tr>
<tr>
<td>$</td>
<td>V_h</td>
<td>$</td>
<td>0.37</td>
<td>——</td>
<td>——</td>
<td>5 h (at 300 m)</td>
<td>RASS</td>
</tr>
<tr>
<td>$T$</td>
<td>0.5</td>
<td>——</td>
<td>800–1000 km</td>
<td>——</td>
<td>Sfc. stations</td>
<td>Land</td>
<td>Gunst 1995</td>
</tr>
<tr>
<td>$T$</td>
<td>0.5</td>
<td>——</td>
<td>200–600 km</td>
<td>——</td>
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<td>Upper air</td>
<td>Nichol and Wong 2008</td>
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<td>$T$</td>
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<td>——</td>
<td>——</td>
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<td>Land</td>
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<tr>
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<td>——</td>
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<td>——</td>
<td>——</td>
<td>12 h</td>
<td>Satellite</td>
<td>Over ITCZ</td>
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Table 3.7: Table 3.6 continued. From Nelson et al. (2019b).

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<td>Airborne</td>
<td>Fisher et al. 2013</td>
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<td>Lidar</td>
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<td>Fisher et al. 2013</td>
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<td>——</td>
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<td>Land</td>
<td>Habib et al. 2001</td>
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<td>——</td>
<td>10 km (NC)</td>
<td>——</td>
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<td>Land</td>
<td>Brigni et al. 2015</td>
</tr>
<tr>
<td>Rain rate</td>
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<td>——</td>
<td>4 km (C)</td>
<td>——</td>
<td>S-band radar</td>
<td>Land</td>
<td>Brigni et al. 2015</td>
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<td>——</td>
<td>1.5–4 km</td>
<td>——</td>
<td>Reports/radar</td>
<td>Land</td>
<td>Jameson 2017</td>
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<td>——</td>
<td>Lidar</td>
<td>Land</td>
<td>Lothon et al. 2006</td>
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<tr>
<td>w</td>
<td>0.2</td>
<td>4–7 km</td>
<td>4–6 km</td>
<td>——</td>
<td>X-band radar</td>
<td>TC eyewall</td>
<td>Black et al. 1996</td>
</tr>
<tr>
<td>w</td>
<td>0.2</td>
<td>2–4 km</td>
<td>1–4 km</td>
<td>——</td>
<td>X-band radar</td>
<td>TC rainband</td>
<td>Black et al. 1996</td>
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</table>

Table 3.8: List of the minimum, maximum, mean, and median dropsonde spacing for each day to the nearest km. From Nelson et al. (2019b).

<table>
<thead>
<tr>
<th>Day</th>
<th>Name</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
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<tr>
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<td>Marty</td>
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<td>21</td>
<td>13</td>
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<td>150</td>
<td>39</td>
<td>41</td>
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<tr>
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<td>344</td>
<td>54</td>
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</tr>
<tr>
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<td>Joaquin</td>
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<td>37</td>
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<tr>
<td>05 Oct</td>
<td>Joaquin</td>
<td>9</td>
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<td>Patricia</td>
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<td>73</td>
<td>22</td>
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</table>
Table 3.9: List of the number of dropsondes within each of the four radial sections and in total on each day. From Nelson et al. (2019b).

<table>
<thead>
<tr>
<th>Day</th>
<th>Name</th>
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<th>1.25–3R$^*$</th>
<th>3–5R$^*$</th>
<th>5–10R$^*$</th>
<th>Total</th>
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<td>20</td>
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<td>Marty</td>
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<td>15</td>
<td>14</td>
<td>58</td>
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<td>Joaquin</td>
<td>15</td>
<td>13</td>
<td>6</td>
<td>10</td>
<td>44</td>
</tr>
<tr>
<td>03 Oct</td>
<td>Joaquin</td>
<td>11</td>
<td>11</td>
<td>7</td>
<td>14</td>
<td>43</td>
</tr>
<tr>
<td>04 Oct</td>
<td>Joaquin</td>
<td>13</td>
<td>16</td>
<td>15</td>
<td>11</td>
<td>55</td>
</tr>
<tr>
<td>05 Oct</td>
<td>Joaquin</td>
<td>9</td>
<td>13</td>
<td>7</td>
<td>24</td>
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<td>21 Oct</td>
<td>Patricia</td>
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<td>18</td>
<td>13</td>
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<td>51</td>
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<td>22 Oct</td>
<td>Patricia</td>
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<td>13</td>
<td>12</td>
<td>13</td>
<td>43</td>
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<tr>
<td>23 Oct</td>
<td>Patricia</td>
<td>5</td>
<td>6</td>
<td>9</td>
<td>8</td>
<td>28</td>
</tr>
</tbody>
</table>

Table 3.10: List of dropsonde-to-dropsonde acceptable spatial autocorrelation thresholds (in km) for each day in the dataset for vertical velocity ($w$), temperature ($T$), horizontal wind speed ($|V_h|$), relative humidity ($RH$), and theta ($\theta$). The size of the RMW (in km) and TC intensity (in m s$^{-1}$) are also noted. From Nelson et al. (2019b).

| Day      | Name   | $w$  | $T$  | $|V_h|$ | RH   | $\theta$ | RMW | Intensity |
|----------|--------|------|------|--------|------|----------|-----|-----------|
| 27 Sept  | Marty  | 3.9  | 7.7  | 5.0    | 4.4  | 6.1      | 37  | 26        |
| 28 Sept  | Marty  | 3.2  | 6.3  | 4.4    | 4.0  | 4.4      | 21  | 36        |
| 02 Oct   | Joaquin| 4.7  | 10.1 | 5.2    | 6.3  | 6.8      | 31  | 57        |
| 03 Oct   | Joaquin| 4.0  | 8.2  | 3.6    | 6.3  | 5.0      | 27  | 67        |
| 04 Oct   | Joaquin| 5.4  | 21.7 | 6.6    | 13.6 | 16.8     | 38  | 44        |
| 05 Oct   | Joaquin| 4.5  | 15.4 | 7.1    | 8.4  | 11.0     | 49  | 39        |
| 20 Oct   | Patricia| 11.2 | 8.6  | 7.1    | 7.5  | 0.6      | 77  | 15        |
| 21 Oct   | Patricia| 4.4  | 14.9 | 5.7    | 7.0  | 10.1     | 40  | 26        |
| 22 Oct   | Patricia| 3.6  | 4.2  | 3.0    | 3.2  | 3.6      | 19  | 59        |
| 23 Oct   | Patricia| 1.9  | 17.1 | 2.6    | 2.3  | 2.1      | 11  | 93        |
| Mean     | ------ | 4.7  | 11.4 | 5.0    | 6.3  | 6.6      | 35  | 46        |
| Median   | ------ | 4.2  | 9.3  | 5.1    | 6.3  | 5.5      | 34  | 41        |
| St. Dev. | ------ | 2.4  | 5.3  | 1.6    | 3.1  | 4.6      | 18  | 22        |
Table 3.11: Same as Table 3.10, but for the acceptable temporal autocorrelation thresholds (in s) for each day in the dataset and any given individual sounding. The size of the RMW (in km) and TC intensity (in m s$^{-1}$) are also noted. From Nelson et al. (2019b).

| Day       | Name       | $w$ | $T$ | $|V_h|$ | RH | $\theta$ | RMW | Intensity |
|-----------|------------|-----|-----|-------|----|--------|-----|-----------|
| 27 Sept   | Marty      | 19  | 25  | 30    | 22 | 14     | 37  | 26        |
| 28 Sept   | Marty      | 23  | 31  | 27    | 24 | 20     | 21  | 36        |
| 02 Oct    | Joaquin    | 23  | 41  | 31    | 27 | 22     | 31  | 57        |
| 03 Oct    | Joaquin    | 25  | 38  | 33    | 35 | 28     | 27  | 67        |
| 04 Oct    | Joaquin    | 22  | 31  | 36    | 23 | 21     | 38  | 44        |
| 05 Oct    | Joaquin    | 20  | 31  | 35    | 21 | 19     | 49  | 39        |
| 20 Oct    | Patricia   | 8   | 21  | 30    | 15 | 12     | 77  | 15        |
| 21 Oct    | Patricia   | 22  | 32  | 26    | 13 | 10     | 40  | 26        |
| 22 Oct    | Patricia   | 21  | 27  | 32    | 17 | 14     | 19  | 59        |
| 23 Oct    | Patricia   | 20  | 33  | 19    | 17 | 16     | 11  | 93        |
| Mean      | ——         | ——  | ——  | 20.3  | 31.0| 29.9 | 21.4 | 17.6   | 35  | 46 |
| Median    | ——         | ——  | ——  | 21.5  | 31.0| 30.5 | 21.5 | 17.5   | 34  | 41 |
| St. Dev.  | ——         | ——  | ——  | 4.4   | 5.5 | 4.7  | 6.1  | 5.1    | 18  | 22 |

Table 3.12: Same as Table 3.11, but for soundings containing an updraft. Also included are the p-values (p) for the Student’s t-test comparisons between the temporal scales in Table 3.11 and the temporal scales in updraft soundings for each variable. From Nelson et al. (2019b).

| Day       | Name       | $w$ | $T$ | $|V_h|$ | RH | $\theta$ | RMW | Intensity | p   |
|-----------|------------|-----|-----|-------|----|--------|-----|-----------|-----|
| 27 Sept   | Marty      | 24  | 28  | 21    | 34 | 29     | 37  | 26        | 0.39|
| 28 Sept   | Marty      | 30  | 42  | 21    | 27 | 25     | 21  | 36        | 0.85|
| 02 Oct    | Joaquin    | 30  | 39  | 22    | 29 | 22     | 31  | 57        | 0.02|
| 03 Oct    | Joaquin    | 25  | 41  | 25    | 46 | 46     | 27  | 67        | 0.11|
| 04 Oct    | Joaquin    | 34  | 38  | 26    | 50 | 54     | 38  | 44        | 0.11|
| 05 Oct    | Joaquin    | 10  | 24  | 28    | 25 | 22     | 49  | 39        | 0.11|
| 20 Oct    | Patricia   | 5   | 19  | 37    | 14 | 11     | 77  | 15        | 0.11|
| 21 Oct    | Patricia   | 33  | 25  | 21    | 27 | 16     | 40  | 26        | 0.11|
| 22 Oct    | Patricia   | 19  | 28  | 20    | 15 | 16     | 19  | 59        | 0.11|
| 23 Oct    | Patricia   | 23  | 32  | 19    | 20 | 16     | 11  | 93        | 0.11|
| Mean      | ——         | ——  | ——  | 23.3  | 31.6| 24.0 | 28.7 | 25.7   | 35  | 46 |
| Median    | ——         | ——  | ——  | 24.5  | 30.0| 21.5 | 27.0 | 22.0   | 34  | 41 |
| St. Dev.  | ——         | ——  | ——  | 9.1   | 7.6 | 5.1  | 11.3 | 13.2   | 18  | 22 |
| p         | ——         | ——  | ——  | 0.39  | 0.85| 0.02 | 0.11 | 0.11   |     |     |
Table 3.13: Same as Table 3.12, but for soundings containing a downdraft. From Nelson et al. (2019b).

| Day      | Name   | w | T  | $|V_h|$ | RH | $\theta$ | RMW | Intensity |
|----------|--------|---|----|------|----|----------|-----|-----------|
| 27 Sept  | Marty  | 8 | 21 | 22   | 10 | 9        | 37  | 26        |
| 28 Sept  | Marty  | 27| 23 | 20   | 23 | 22       | 21  | 36        |
| 02 Oct   | Joaquin| 26| 41 | 25   | 28 | 24       | 31  | 57        |
| 03 Oct   | Joaquin| 32| 47 | 43   | 67 | 65       | 27  | 67        |
| 04 Oct   | Joaquin| 0 | 0  | 0    | 0  | 0        | 0   | 38        |
| 05 Oct   | Joaquin| 0 | 0  | 0    | 0  | 0        | 0   | 49        |
| 20 Oct   | Patricia| 27| 19 | 15   | 18 | 17       | 77  | 15        |
| 21 Oct   | Patricia| 21| 31 | 24   | 21 | 14       | 40  | 26        |
| 22 Oct   | Patricia| 22| 34 | 48   | 40 | 36       | 19  | 59        |
| 23 Oct   | Patricia| 20| 71 | 18   | 17 | 14       | 11  | 93        |
| Mean     |        | 22.9| 35.9| 26.9 | 28.0 | 25.1 | 35 | 46        |
| Median   |        | 24.0| 32.5| 23.0 | 22.0 | 19.5 | 34 | 41        |
| St. Dev. |        | 6.7 | 16.1| 11.2 | 16.9 | 16.9 | 18 | 22        |
| p        |        | 0.40| 0.34| 0.52 | 0.35 | 0.29 |     |           |

Table 3.14: Number of updraft (U) and downdraft (D) soundings for each day. From Nelson et al. (2019b).

<table>
<thead>
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<th>Day</th>
<th>Name</th>
<th>U</th>
<th>N</th>
</tr>
</thead>
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<td>Marty</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>28 Sept</td>
<td>Marty</td>
<td>9</td>
<td>5</td>
</tr>
<tr>
<td>02 Oct</td>
<td>Joaquin</td>
<td>13</td>
<td>15</td>
</tr>
<tr>
<td>03 Oct</td>
<td>Joaquin</td>
<td>15</td>
<td>4</td>
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<td>04 Oct</td>
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<td>Joaquin</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>20 Oct</td>
<td>Patricia</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>21 Oct</td>
<td>Patricia</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>22 Oct</td>
<td>Patricia</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>23 Oct</td>
<td>Patricia</td>
<td>12</td>
<td>6</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>78</td>
<td>37</td>
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</table>
Figure 3.29: Median atmospheric profiles of (a, b, c, d) $w$ (m s$^{-1}$), (e, f, g, h) $|V_h|$ (m s$^{-1}$), and (i, j, k, l) RH (%) during Marty for data (a, e, i) within 1.25R$^*$, (b, f, j) 1.25–3R$^*$, (c, g, k) 3–5R$^*$, and (d, h, l) 5–10R$^*$. From Nelson et al. (2019b).
Figure 3.30: Same as Fig. 3.29, but of (a, b, c, d) $T$ (K) and (e, f, g, h) $\theta$ (K). From Nelson et al. (2019b).
Figure 3.31: Same as Fig. 3.29, but for Joaquin. From Nelson et al. (2019b).
Figure 3.32: Same as Fig. 3.30, but for Joaquin. From Nelson et al. (2019b).
Figure 3.33: Same as Fig. 3.29, but for Patricia. From Nelson et al. (2019b).
Figure 3.34: Same as Fig. 3.30, but for Patricia. From Nelson et al. (2019b).
Figure 3.35: Comparison of the (a) acceptable daily dropsonde-to-dropsonde horizontal autocorrelation length scale (km) to the RMW (km), and (b) acceptable daily dropsonde-to-dropsonde horizontal autocorrelation length scale to the acceptable daily temporal autocorrelation length scale (s) for $w$, $T$, $|V_h|$, $RH$, and $\theta$ (black, red, blue, green, and dark red, respectively). The 1:1 (or $x = y$) line (black) is shown in (a). From Nelson et al. (2019b).
Figure 3.36: Temporal and spatial autocorrelations for XDDs launched into Marty. Panel (a) shows the spatial autocorrelation correlograms for $w$, $|V_h|$, $RH$, $T$, and $\theta$ (black, blue, green, red, and dark red, respectively). Panel (b) shows the 0.5-autocorrelation length scales for each variable as a function of altitude. Panel (c) shows the temporal autocorrelation correlograms for $w$, $|V_h|$, $RH$, $T$, and $\theta$. Panel (d) shows the 0.5-autocorrelation temporal scales for each variable as a function of radius. Correlations of 0.5 and 0.0 are denoted in panels (a, c) with dashed red and black lines, respectively. From Nelson et al. (2019b).
Figure 3.37: Same as Fig. 3.36, but for Joaquin. From Nelson et al. (2019b).
Figure 3.38: Same as Fig. 3.36, but for Patricia. From Nelson et al. (2019b).
Figure 3.39: Vertical profiles of (a) $w$, (b) $|V_h|$, (c) RH, (d) $T$, and (e) $\theta$ from an updraft sounding (dropsonde 72CC) launched into the eyewall of Patricia on 23 October. The red horizontal lines denote the depth of the updraft. From Nelson et al. (2019b).
Figure 3.40: Same as Fig. 3.39, but with respect to time. From Nelson et al. (2019b).
Figure 3.41: Same as Fig. 3.39, but for profiles of perturbation (a) $w$, (b) $|V_h|$, (c) $RH$, (d) $T$, and (e) $\theta$. From Nelson et al. (2019b).
Figure 3.42: Temporal autocorrelation correlograms of (a) \(w\) (black), (b) \(|V_h|\) (blue), (c) RH (green), (d) \(T\) (red), and (e) \(\theta\) (dark red). Correlations of 0.5 and 0.0 are denoted with horizontal dashed red and black lines, respectively. Correlograms for the single updraft sounding in Figs. 3.39–3.41 are in solid color lines, and correlograms for all soundings on 23 October are in dashed color lines. From Nelson et al. (2019b).
Figure 3.43: 0.5-autocorrelation temporal thresholds for (a) $w$, (b) $|V_h|$, (c) $RH$, (d) $T$, and (e) $\theta$ within individual soundings that recorded an updraft as a function of maximum updraft depth in the sounding. Correlations and linear fits (red lines) are also provided. From Nelson et al. (2019b).
Figure 3.44: Same as Fig. 3.43, but for individual downdraft soundings. From Nelson et al. (2019b).
CHAPTER 4
Computational fluid dynamics modeling

4.1 Introduction and methods

Prior to performing any physical drop tests of the new XDDs with the low-dP sensors, three-dimensional modeling of the typical airflow and pressure anomaly distribution around a falling XDD was examined. A three-dimensional model of the XDD implemented into a basic computational fluid dynamics (CFD) model is useful to obtain estimates of optimal port location, pitot-static calibration coefficients (ratio of the true airspeed to the IAS), drag force, and errors associated with angle of attack. A three-dimensional model of the XDD itself, obtained from computer-aided design and drafting (CAD) files provided by Yankee Environmental Systems, was imported into the ‘simFlow’ three-dimensional CFD (Fig. 4.1). The three-dimensional model is not a perfect representation of the XDDs or their fall characteristics, but it is reasonable to use the CFD for basic simulations and to estimate the behavior of the XDD as it falls. The CAD file itself is not included in this dissertation due to proprietary concerns.

*simFlow* has been established as an adequate and robust CFD modeling software package (e.g., Lodh et al., 2017). *simFlow* uses the *ParaView* and *OpenFOAM* open source tools, which are commonly used in engineering studies. It can model both incompressible and compressible flows, include turbulence, simulate heat transfer, and include simple chemical reactions. All values of pressure, wind speed, and turbulence are normalized by the density of the fluid even though the units for these values are reported as Pa, m s$^{-1}$, and J,
respectively.

In order to compute the wind flow around the XDD as it falls, and the pressure perturbations observed during descent, a non-uniform gridded mesh of the XDD and the space around the XDD was created (Fig. 4.2). simFlow creates the non-uniform gridded mesh from a user defined initial fixed grid. The specifications for the mesh size and CFD are provided in Table 4.1. The CFD model was run for 250 s with a 1-s time step, incompressible free-stream airflow of 20 m s$^{-1}$, and Reynolds-averaged NavierStokes (RANS) k-ω shear stress transport (SST) turbulence. The RANS k-ω SST turbulence model performs well in conditions of adverse pressure gradients or separating flows around an object and in both high and low Reynolds number situations (Menter, 1993). Adverse pressure gradients occur when the pressure increases in the direction of the flow, such as for an XDD falling through the atmosphere in a motion-relative, Langrangian framework (e.g., Figs. 4.3c, 4.4c). The CFD was also run at free-stream airflows of 20 m s$^{-1}$ at different angles of incidence from 0–360°, every 5° to simulate the behavior of the XDD as it falls near terminal fall speed. Note that in simFlow, the horizontal axes are $x$ and $z$ and the vertical axis is $y$.

4.2 Results

4.2.1 Airflow characteristics

The CFD shows that at 20 m s$^{-1}$ true, the apparent airflow decreases to approximately 10 m s$^{-1}$ at the nose of the XDD, which corresponds to an increase in pressure of 170–215 Pa (Figs. 4.3a, c, 4.4a, c). The flow diverges around the nose and either enters the twisted slots in the foam or flows parallel the contours of the dropsonde body (Figs. 4.3b, 4.4b). There is a slight increase in the apparent airspeed outside of the dropsonde body along the sides, which corresponds to a relatively weak low-pressure anomaly along the sides of the dropsonde
body (Figs. 4.3a, c, 4.4a, c). The flow then converges in the aft of the dropsonde and weak wake low pressure anomalies form, with high turbulent kinetic energy (TKE) approximately half an inch behind the quadrifilar antenna and rotation of the airflow immediately behind the foam body (Figs. 4.3b, c, d, 4.4b, c, d). The low-pressure anomaly in the aft dissipates quickly, indicating that the pressure recovery is quick for the XDDs and that the low pressure is not appreciably strong, deep, or steady in the aft of the dropsonde (Figs. 4.3c, 4.4c). The airflow immediately behind the quadrifilar antenna is relatively calm, with weak airflow and a weak, but steady, 30–40 Pa low-pressure anomaly (Figs. 4.3a, c, d, 4.4a, c, d).

The tail of the dropsonde (Fig. 4.5) has four pockets of strong negative pressure anomalies at −80 to −90 Pa associated with the blocked flow from the foam body of the XDD (Fig. 4.5c) and a weaker, −30 to −40 Pa, pocket of low pressure behind the antenna (Fig. 4.5a). But, these negative pressures are comparable to the negative pressures along the side of the dropsonde body (e.g., Fig. 4.5c), which would produce a weak or near-zero differential pressure for the venturi-static methods. Weak or near-zero differential pressures are more prone to large percent errors associated with signal saturation as previously described in Section 2.4. This means that the venturi-static method may not work well despite being the least prone to icing conditions.

A venturi port somewhere in the aft of the XDD is still plausible if a pitot-venturi method was used. Even though there is appreciable turbulence associated with the wake low in towards the aft of the XDD, the high TKE zone is far enough away from the end of the antenna (Fig. 4.3d) and the negative pressure anomaly and airflow strength immediately behind the antenna is reasonably uniform (Fig. 4.5a, b) to justify an antenna venturi port. Further, the low pressure and airspeed behind the antenna is more uniform than the low pressure and airflow behind the foam body of the XDD (Fig. 4.5c, d) and the rotor-like
feature in the airflow behind the foam body is problematic (Fig. 4.3b), which suggests that a venturi port at the end of the quadrifilar antenna would be the most optimal venturi method. The strength of the low-pressure anomaly behind the from a single body aft port to one side of the antenna is also a stronger function of the angle of incidence of the XDD to the flow (Fig. 4.8, discussed below) and, subsequently, the phase of the XDD in its' rotation, which complicates the analysis of the IAS data.

The variance in the low pressure along the sides of the dropsonde presents a challenge for the pitot-static method. If a pitot-static was used, then the static port should be located towards the back end of the foam body to obtain a pressure measurement closer to the true static air pressure (0 Pa; Figs. 4.3c, 4.4c). A side static port is also logistically and operationally challenging, because of the effort it takes to route the pitot tube around the circuit board and electronics and puncturing the side wall of the XDD sleeve (Table 2.1). The pitot-static method would also suffer the same strong angle of incidence and dropsonde rotation issues as the pitot-venturi with a body venturi. This makes the pitot-static method arduous despite the hypothesis that it would be more resilient to icing.

The nose of the dropsonde has little variance in dynamic pressure caused by the airflow (Fig. 4.6a, b). The pressure along the leading edge/nose of the dropsonde foam body varies by approximately 20 Pa, but along the central line (shown in black in Fig. 4.6a, b) it only varies by 1–5 Pa at most. The largest dynamic pressures occur in the area between the nose and side wall and the corners of the rounded nose (Fig. 4.6a). This means that little variation in the pressure should exist with port placement along the central line of the nose of the dropsonde and that the two pitot methods should be highly reproducible from dropsonde-to-dropsonde. These results indicate that the IAS from a pitot-static would more closely represent the true airspeed, but the operational limitations and analytical issues
of the pitot-static make it realistically infeasible for use on the XDDs. The pitot-venturi method with an antenna port, therefore, is likely the most robust methodology out of the three modeled in the CFD, despite its limitations (Table 2.1).

The results from the CFD indicate that any method used would not accurately obtain the true airspeed without a calibration coefficient. Because the pitot-venturi method appears to be the most reproducible and most operationally viable method, it was tested to estimate an airspeed calibration coefficient by placing ‘zero-mass’ pressure probes on the nose and the antenna at the geometric center of the dropsonde and an aft body probe to one side of the XDD (Fig. 4.7). These probes report the exact pressure at a specific location in the CFD output without adding in an actual probe to the XDD model. The pitot-venturi method was compared to the venturi-static method and both were rotated with respect to both of the vertical planes (x-y plane and z-y plane) to examine the impact of dropsonde tilt or tumbling on the differential pressure.

The calibration coefficient ($P^*$) for each method is calculated by:

$$P^* = \frac{0.5V^2}{dP},$$  \hspace{1cm} (4.1)

note that density is not included in the calculation, because the differential pressure obtained from the CFD is normalized by density. In order to obtain the true airspeed, one would need to multiply the observed differential pressure by $P^*$. The estimated $P^*$ value for the pitot-venturi with the tail venturi port is 0.97, which is larger than for the pitot-venturi with the body venturi port at 0.81. This means that the pitot-venturi with the body port should overestimates the airspeed by approximately 20%, whereas the pitot-venturi with the tail port is closer to the true airspeed.
Figure 4.8 shows the response of the differential pressure for the pitot-venturi method with an antenna port or a body port to the angle of incidence. The model XDD was rotated in both the x-y plane and the x-z plane and the average zero-incidence normalized signal ($S^*$) was plotted. Cross sections of the typical airflow and pressure at incidences of 0, 90, 180, and 270° in both the x-y and z-y plane are provided in Figures 4.9 and 4.10. $S^*$ rises slightly above unity over an 80° span (±40°), then decreases rapidly to zero at approximately ±80°. At large incidences to the flow, the signal changes sign and indicates an incorrect, negative differential pressure that minimizes at incidences of 140 and 220°. The pitot-venturi method with an antenna port has $S^*$ values closer to unity at ±40° incidences, but stronger (more negative) $S^*$ values outside of the ±40° incidences (Fig. 4.8). The pitot-venturi method with an antenna port has errors within ±0.5 m s$^{-1}$ at ±5° incidences and ±1 m s$^{-1}$ at ±10°. The angle of incidence, therefore, is an appreciable error that can affect the measurement beyond the desired error budget of ±0.1 m s$^{-1}$. At present, the severity of the tilt of the XDDs during descent is not known and further study of dropsonde dynamics is needed to obtain a realistic measure of tilt effects on the IAS measurement. Measurements of dropsonde tilt during descent can also be used to make adjustments to the measured differential pressure IAS, which would account for most of these errors.

### 4.2.2 Drag coefficient estimate

The simFlow CFD model monitors density normalized drag forces ($F^*$) in the three-dimensional framework (x, y, z). The drag coefficient can then be obtained using a modified version of equation 2.9:

$$C_d = \frac{2F^*}{AV^2},$$

(4.2)
for each x, y, and z component. The drag coefficient was computed at airspeeds of 20 m s$^{-1}$ and in both for axial (nose-on) and cross-flows (side-on). The frontal area of the XDD can be approximated as a circle, with a diameter of 0.066 m (Black et al., 2017). The side area of the XDD can be approximated by rectangle with a length of 0.178 m and a width of 0.066 m (Black et al., 2017).

Using these approximated areas, the CFD indicated drag coefficient for the XDDs in axial flow (y-direction) is 0.93, which is close to the 0.95 estimate in Section 2.4. Both values for the nose-on drag coefficient are slightly larger than what is expected for a cylinder in axial flow by approximately 0.1–0.15 for a length to diameter ratio for the XDDs of 2.7 (Higuchi et al., 2006). The drag coefficient for cross-flow (x-, z-direction) is an average of 1.30, which is not appreciably different than the axial drag coefficient and is representative for a smooth cylinder in cross-flow at the expected Reynolds numbers for the XDDs (Fig. 2.13) (e.g., Munson et al., 2006).

<table>
<thead>
<tr>
<th>Table 4.1: Specifications for the simFlow CFD for the XDDs.</th>
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<tbody>
<tr>
<td><strong>Value or description</strong></td>
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<tr>
<td>Time</td>
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<td>Duration</td>
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<tr>
<td>Compression</td>
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<tr>
<td>Airspeed</td>
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<td>Wind direction</td>
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<td>Turbulence</td>
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<td>Boundary conditions</td>
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<td>Number of initial grid points</td>
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<td>Grid spacing (x; z; y)</td>
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<td>Transport model</td>
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<td>Solver</td>
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</table>
Figure 4.1: Three-dimensional model of the XDDs provided by Yankee Environmental Systems.
Figure 4.2: Three-dimensional non-uniform grid (brown and green in panel (a) and mesh around the XDDs (orange in panel (b))). Note, the vertical axis is denoted in simFlow a ‘y’ rather than the traditional ‘z’.

Figure 4.3: Results of the CFD at zero angle of incidence in the x-direction. Panel (a) is the airflow (m s$^{-1}$; shaded). Panel (b) shows the streamlines of the airflow, with the airspeed shaded in m s$^{-1}$. Panel (c) is the anomalous pressure relative to the ambient pressure (Pa; shaded). Panel (d) is TKE (J; shaded).
Figure 4.4: Same as Fig. 4.3, but for the z-direction.

Figure 4.5: Anomalous pressure (Pa; shaded) and airflow (m s$^{-1}$; shaded) behind the main body of the dropsonde. Panels (a) and (b) are immediately behind the quadrifilar antenna, whereas panels (c) and (d) are immediately behind the foam body of the dropsonde.
Figure 4.6: Anomalous pressure (Pa; shaded) and airflow (m s$^{-1}$; shaded) at the nose of the dropsonde. The center-line of the XDD foam body is shown as a dashed black line.

Figure 4.7: Location of pressure probes/ports for the CFD analysis. The nose pitot port is the red dot in panel (b), the antenna venturi port is the green dot in panel (a), and the venturi body port is the purple dot in panel (a).
Figure 4.8: Polar plot of $S^*$ for the pitot-venturi with the antenna port (blue) and the body port (red). $S^*$ values of 1 and 0 are highlighted in black and green, respectively.
Figure 4.9: Airflow around the XDD as it falls (m s$^{-1}$; shaded) rotated in the x-y plane. Panel (a) is at an angle of 180°, panel (b) is at an angle of 90°, panel (c) is at an angle of 0°, and panel (d) is at an angle of 270°.
Figure 4.10: Same as Fig. 4.9 but rotated in the z-y plane.
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