ABSTRACT

YAZDANI BOROUJENI, BEHDAD. Road Grade Quantification Using GPS in On-Board Vehicle Emission Measurements. (Under the direction of H. Christopher Frey.)

Real-world vehicle tailpipe emissions constitute an important portion of ambient air pollution. NO_x, CO_2, CO, and hydrocarbons are among the main gaseous pollutants that are emitted from vehicles. Vehicle fuel consumption and pollutant emissions vary with road grade. Vehicle Specific Power (VSP) indicates the engine load and is a function of speed, acceleration, and road grade. Fuel use and emission rates are sensitive to VSP. Ang and Fwa (1989) identified road grade as an important factor influencing vehicle fuel use and emissions. Zhang and Frey reported that NO_x emission rates are 4 times higher when driving on a road with +5 percent grade compared to a flat road at a speed of between 35 to 45 mph.

In on-board vehicle emissions measurement studies, Global Positioning System (GPS) receivers are used for quantifying position and elevation changes while driving to calculate road grade. However, GPS receivers suffer from inaccuracy especially in reporting true elevation. GPS signals are subject to random errors related to satellite coverage at a given time and variations in atmospheric attenuation. Furthermore, depending on receiver location and local topography, signals may be blocked by buildings, bridges, or forest canopies. GPS receivers differ with respect to accuracy. However, typically, receivers that are more accurate are also more prone to signal loss when operated from a moving vehicle in an urban or forested area; less accurate receivers have little signal loss.

A Differential GPS (DGPS) system with base and rover stations can provide a much

more accurate estimate of position and elevation than a stand-alone receiver. Wing and Frank tested the vertical accuracy of mapping-level Trimble GeoXH 3,000 Series DGPS receivers with base and rover stations. They reported an average error of ±0.4 meters after post-processing data in open sky areas and an average error of ±3.1 meters after post-processing data in forest canopy areas. However, when taking measurements from a moving vehicle in an urban area, the accuracy in elevation needed to estimate road grade needs to be better than ±3.1 meters. For example, if over a 100 meter true distance the change in true elevation is 5 meters, an error of ±3 meters in position will lead to a range of grade estimates of approximately 4.5 to 5.5 percent. However, an error of ±3 meters in elevation will lead to a range of grade estimates of approximately +2 to +8 percent.

As an alternative to the use of an expensive (e.g., $15,000) DGPS system, a low cost (e.g., $250) stand-alone consumer grade GPS receiver with barometric altimeter (CGPS/BA) can be used for measuring relative changes in elevation. The horizontal accuracy of this receiver is approximately ±3 meters, and in practice this receiver rarely experiences complete loss of signal for latitude and longitude. The vertical accuracy is approximately ±2 meters and the altimeter is not subject to loss of signal. While the CGPS/BA is less accurate than the DGPS when operating in areas with no loss of signal, it may provide better estimates of road grade when operating in areas where the accuracy of DGPS elevation is affected by structures and canopies. The CGPS/BA could also be deployed as a backup to DGPS to fill in missing data when the DGPS rover station experiences a loss of signal.

Road Grade Quantification Using GPS in On-Board Vehicle Emission Measurements

by
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DEDICATION

To My Parents:

Vajiheh & Bahador,

And My Lovely Sister:

Niloofar

BIOGRAPHY

Behdad Yazdani Boroujeni was born in 1987 in Mashhad, Iran. In 2005, he was admitted to the Civil Engineering program at Sharif University of Technology. He joined the Department of Civil, Construction, and Environmental Engineering at North Carolina State University in August 2010 to pursue a Master of Science degree. His research focuses on the measurement of energy use and emissions in the transportation sector and quantifying accurate and precise estimates of road grade based on GPS data. This thesis completes the requirements for that degree.

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Chapter 1

Introduction

On-board vehicle emissions measurement methods have gained popularity in the last decade (Frey et al. 2003; Coelho et al. 2009). In-use measurements enable quantification of emissions under representative operating conditions. Portable Emissions Measurement Systems (PEMS) have been used to measure the real-world tailpipe concentrations of NO_x, CO, CO_2, and hydrocarbons. Real-world on-road vehicle emissions depend on engine load, which is affected by vehicle speed, acceleration, and road grade (Yazdani et al. 2012; Zhang and Frey 2006). These latter three variables are used to calculate Vehicle Specific Power (VSP), which takes into account kinetic energy, climbing resistance on a hill, rolling resistance, and aerodynamic drag (Huai et al. 2005; Frey et al. 2006; Jiménez-Palacios 1999). Recently developed emissions models, such as the MOtor Vehicle Emission Simulator (MOVES) model released in 2009 by the U.S. Environmental Protection Agency (EPA), use second-by-second speed, acceleration, and road grade for any user supplied driving schedule to calculate second by second VSP (Lindhjem et al. 2004; Koupal et al. 2004). Speed and acceleration depend on traffic flow conditions, driver behavior, and road type and can be obtained from the Electronic Control Unit

(ECU) of the vehicle on a second-by-second basis. Road grade is a property of the road infrastructure. Currently, there is no standardized procedure for quantifying road grade on a second-by-second basis.

Road grade is the change in elevation divided by the distance traveled, usually expressed in percent. Positive road grade means that the road elevation increases with distance (uphill). Negative road grade means that road elevation decreases with distance (downhill). For flat roads, road grade is zero. Boriboonsomsin and Barth (2009) showed that on average, fuel use increases by 15 to 20 percent when a typical light duty vehicle is driven over a hilly road with +6 percent grade compared to a flat road. Vehicle fuel use or emissions increase with increasing road grade (Pierson et al. 1995; Cicero-Fernandez and Long 1997; Kelly and Groblicki 1993). Zhang and Frey (2006) measured fuel use rates higher by 40 to 90 percent and emission rates for NO_x, CO, and hydrocarbons (HC) higher by 60 to 450 percent for three light duty gasoline vehicles when comparing a flat surface versus grades $\geq +5$ percent.

Road grade can be quantified based on various data sources, including design drawings, LIght Detection And Ranging (LIDAR), accelerometer, inclinometer, and Global Positioning System (GPS) receiver (Yazdani et al. 2012; Zhang and Frey 2006; Boriboonsomsin and Barth 2009; Graver et al. 2011; Rogers and Trayford 1984; Heywood et al. 2006). Design drawing is an initial scheme of the road that shows its scope and conceptual design including road grade. Design drawings may be available only for large road facility projects such as freeways (Yazdani et al. 2012; Zhang and Frey 2006). LIDAR is a remote sensing system that utilizes aircraft-mounted lasers to collect topographic data for road surfaces over large topographic areas. Lasers used in this method are capable of

estimating elevation within 15 cm and position within 2 meters of the true coordinate. LIDAR has been used to create Digital Elevation Models (DEMs) (Zhang and Frey 2006; Heywood et al. 2006). Accelerometers can be used onboard to make inferences along a path driven by a vehicle, but are subject to confounding because of movements of the vehicle suspension (e.g. because of bumps or potholes) that are not related to grade (Rogers and Trayford 1984). Likewise, inclinometers are useful for making static measurements but are subject to random error when used in a moving vehicle (Yazdani et al. 2012; Mangan et al. 2002). GPS receivers can provide second-by-second records of vehicle position and elevation, but are subject to a variety of errors detailed later (Heywood et al. 2006; Wing et al. 2005).

To support analysis of PEMS-based emissions data with respect to variation in engine load, it is necessary to quantify road grade along the path driven by the vehicle. While LIDAR and design drawing data can offer some advantages over in-vehicle measurement methods, they are not typically available at any location driven by a vehicle. Although accelerometers and inclinometers could be used to infer grade on a continuous basis during vehicle operation on a given path, they are not sufficiently accurate when used in a moving vehicle. Accuracy refers to agreement between the average of repeated measurements and the true value of the quantity being measured. Precision refers to the lack of random error spread in repeated measurements of the same quantity. There is need for a practical method to quantify road grade with sufficient accuracy and precision at every location along a route for which PEMS measurements are made. Here, GPS receivers are explored and evaluated as one of the more promising sources of such data.

GPS data include time, latitude (ϕ), longitude (λ), and elevation (Z). GPS data for

position, even from low cost receivers, tend to be accurate up to ±2 meters, and various measurement and analysis techniques are available with higher accuracy. However, low cost receivers tend to be inaccurate for elevation, with errors of 20 meters or more at some locations. Thus, it can be impractical to estimate changes in elevation from one location to another unless the accuracy of Z can be improved. Here, we explore two approaches for improving estimates of Z.

GPS receivers are classified depending on their purpose and capabilities. For example, consumer grade GPS receivers are usually less than US $1,000 and can provide position (ϕ and λ) accuracy to within 20 to 2 meters (Wing et al. 2005). All GPS receivers estimate position data (ϕ and λ) from satellite signals. However, elevation may be obtained either by using the GPS satellite signal or by using in-built barometric altimeter available in some GPS receivers. Using the GPS satellite signal with a stand-alone receiver in a moving vehicle will usually lead to large vertical errors of as much as ±20 meters or more. Large vertical errors happen if satellite configuration used for location calculations changes or satellite signals are obstructed by bridges, buildings, or trees (McBurney and Braisted 2000). In contrast, a barometric altimeter can provide estimates of relative changes in elevation to within ±2 meters. A barometer responds to change in atmospheric pressure; atmospheric pressure decreases with increasing altitude (Yazdani et al. 2012).

Mapping grade GPS units are accurate from about 5 meters to 0.3 meters in absolute position and elevation. They typically cost between US $2,000 to US $12,000 (Wing et al. 2005). Surveying grade GPS receivers can estimate position and elevation within 10 centimeters or better accuracy. They cost more than US $12,000. Mapping and survey-

ing grade GPS receivers typically include differential correction to one or more GPS base stations, which significantly improves accuracy (Sickle 2008; Ogaja 2011). A Differential GPS (DGPS) consists of base and rover stations. Base stations are one or more GPS receivers at locations with known coordinates. The rover station is a mobile receiver located in the moving vehicle. Rover station data are corrected to base station data either in real-time or by post-processing. Since the base and rover stations are close to together, i.e. a few tens of kilometers, compared to each of their distances from the GPS satellites, i.e. approximately 20,000 kilometers, the comparison between them helps eliminate common errors associated with the satellite signals, thereby improving accuracy (Ogaja 2011).

DGPS networks comprised of multiple base stations have been set up in many regions of the United States. Most of such DGPS networks are operated on a commercial or governmental basis where the base stations continuously exchange measurements and check on each other. This ensures higher network reliability, such that errors in a single base station can be easily detected. In addition, it is possible to use combined error corrections from several base stations, in a technique known as Virtual Reference Station (VRS) network solution. In VRS network, which is a real-time processing technique, a number of nearby base stations measure the range corrections and transmit them to a central processing hub. The hub then combines the data from various base stations into one solution set of range corrections. The combined set of errors is transmitted via a data link such as high speed Internet to the rover station, where the range corrections are applied to the measured parameters. In another form of centralized hub processing, multiple base stations are included in a post-processing solution for which real-time communication between rover station and the central hub is not needed (Ogaja 2011).

The purpose here is to:

1. Determine the accuracy and precision of GPS in estimating distance traveled,
2. Develop a technique to calculate road grade from raw GPS data,
3. Determine the precision of estimated road grade obtained from GPS receiver,
4. Identify relationships between precision and factors such as number of repeated runs and magnitude of road grade,
5. Benchmark comparison of the estimated GPS-based road grade to independent data sources such as LIDAR-based road grade.

Chapter 2

Methodology

This chapter describes vehicle specific power and its sensitivity to road grade, sensitivity of vehicle fuel use and emissions to engine load, methods for measuring road grade, GPS instrumentation, study design and field data collection, and data analysis.

2.1 Vehicle Specific Power and Sensitivity to Road Grade

Vehicle specific power (VSP) accounts for the resistance forces that the vehicle must overcome to move, including: 1) inertial resistance, 2) climbing resistance, 3) rolling resistance, and 4) aerodynamic resistance, Figure 2.1.

VSP is given by (Jiménez-Palacios 1999):

$$\text{VSP} = v\big[(1+\epsilon)a + g\big(\frac{r}{100}\big) + gC_R\big] + \frac{1}{2}\rho_{air}v^3\left(\frac{C_D A}{m}\right) \tag{2.1}$$

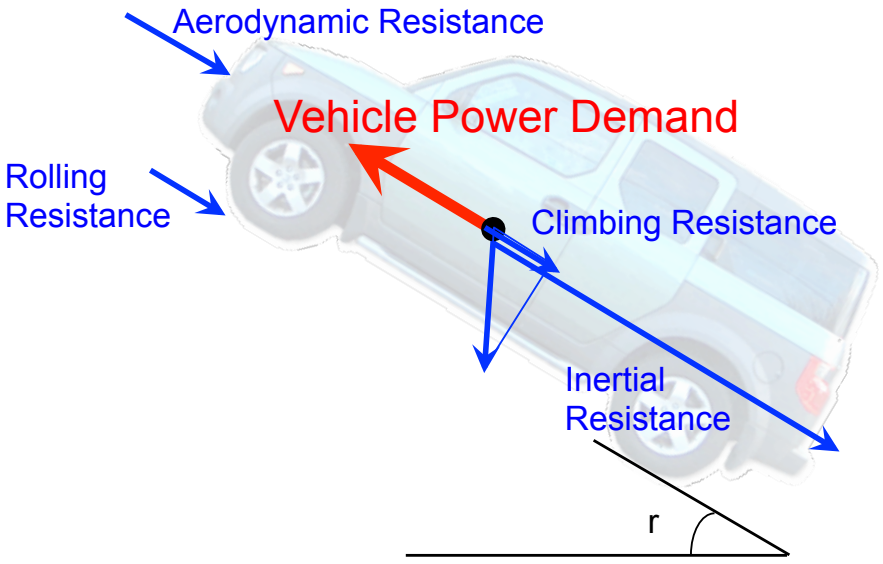


Figure 2.1: Resistance forces on vehicle and vehicle specific power.

where:

a	=	Vehicle acceleration, (m/s^2)
A	=	Vehicle frontal area, (m^2)
C_D	=	Aerodynamic drag coefficient, (dimensionless)
C_R	=	Rolling resistance coefficient, (dimensionless, ~ 0.0135)
g	=	Acceleration of gravity, (9.81 m/s^2)
m	=	Vehicle mass, (metric ton)
r	=	Road grade, (%)
v	=	Vehicle speed, (m/s)
VSP	=	Vehicle Specific Power, (kW/metric ton)
ϵ	=	Factor accounting for rotational masses, (~ 0.1)
ρ_{air}	=	Ambient air density, (1.207 kg/m^3 at 20 °C).

For a typical light duty vehicle, a simplified version of Equation 2.1 is usually used:

$$\text{VSP} = v\big[1.1a + 9.81\big(\frac{r}{100}\big) + 0.132\big] + 0.000302v^3 \tag{2.2}$$

Because the trend in emission rates differs among different pollutants, empirically-based modal emissions models have been widely adopted to quantify the trend in emissions rates versus VSP (Huai et al. 2005; Frey et al. 2006; Jiménez-Palacios 1999; Lindhjem et al. 2004; Koupal et al. 2004). Based on detailed statistical analyses of trends in CO_2, CO, NO_x, and hydrocarbon (HC), Frey et al. (2002) developed 14 VSP modes that enable quantification of linear and nonlinear trends versus VSP and for which each mode includes a significant share of typical driving cycles, as shown in Table 2.1.

Whereas vehicle speed can be accurately obtained from the Electronic Control Unit (ECU), and acceleration can be inferred from differences in speed from one second to another, road grade is not available from the ECU or PEMS and must be obtained some other way. To illustrate the importance of road grade to engine power demand, a sensitivity analysis is conducted in which road grade and speed are varied.

Table 2.1: Definition of Vehicle Specific Power (VSP) Modes (Frey et al. 2002)

VSP Mode	**Range Definition**	**VSP Mode**	**Range Definition**
1	$\text{VSP} < -2$	8	$13 \leq \text{VSP} < 16$
2	$-2 \leq \text{VSP} < 0$	9	$16 \leq \text{VSP} < 19$
3	$0 \leq \text{VSP} < 1$	10	$19 \leq \text{VSP} < 23$
4	$1 \leq \text{VSP} < 4$	11	$23 \leq \text{VSP} < 28$
5	$4 \leq \text{VSP} < 7$	12	$28 \leq \text{VSP} < 33$
6	$7 \leq \text{VSP} < 10$	13	$33 \leq \text{VSP} < 39$
7	$10 \leq \text{VSP} < 13$	14	$39 \leq \text{VSP}$

2.2 Sensitivity of Vehicle Fuel Use and Emissions to Engine Load

Vehicle specific power is sensitive to road grade. To quantify the importance of road grade to emissions for a driving cycle, Frey and Zhang (2007) demonstrated the use of three scenarios for which estimates are done assuming zero grade and, in comparison, assuming actual grade: (1) only segments of the cycle that have negative grade; (2) only segments of the cycle that have positive grade; and (3) the entire cycle. The effect of road grade on increasing emissions along segments with positive grade, and on decreasing emissions along segments with negative grade, is quantified by comparing estimates made with actual grade versus zero grade. Similarly, the overall effect of accounting for road grade on the entire driving cycle is quantified by comparing estimated emissions based on actual grade to those based on zero grade.

Figure 2.2 shows an example of fuel use and emissions modal results for a typical light duty vehicle; road grade used here is based on averaging 100 runs of low cost GPS data which will be discussed later. Fuel use and emissions (g/s) in VSP modes 1 and 2 are small and approximately constant (Lee and Frey 2012). Road grade is not important during idling in VSP mode 3 because the vehicle is stationary. Fuel use and emissions increase monotonically among VSP modes 3 to 14 that have increasing positive VSP (Lee and Frey 2012; Xu et al. 2010; Frey et al. 2008). For this particular example, the trend in fuel use rate versus positive VSP is approximately linear, as expected, and the trend in NO_x emissions rate versus positive VSP is monotonic and nonlinear. For CO and HC, the trends are also approximately monotonic and nonlinear with positive VSP. However, the sample size of 1 Hz measurements is relatively small at VSP modes 11 to 14, and

there are random statistical artifacts in the trend (Lee and Frey 2012; Frey et al. 2008).

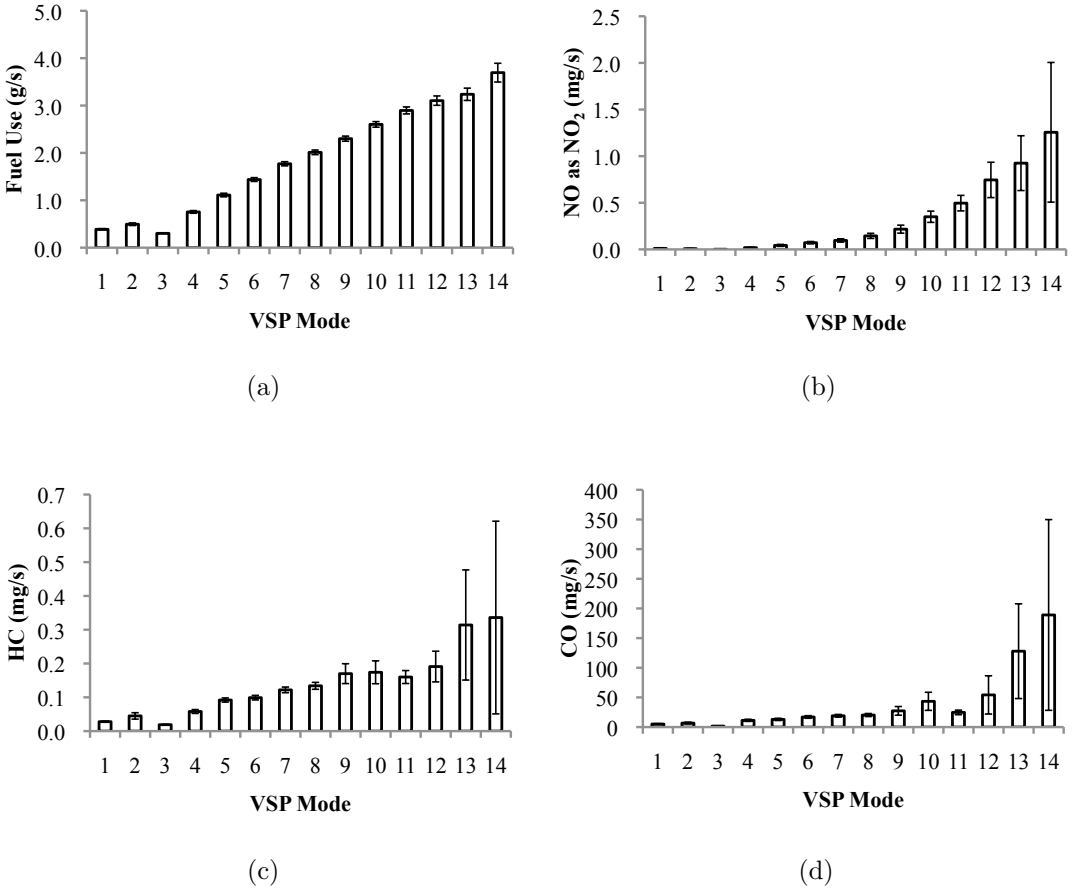


Figure 2.2: An example of VSP modal average fuel use and emission rates with 95% confidence interval on mean for a 2011 Chevrolet HHR based on PEMS data. Road grade used here is obtained from averaging 100 runs of low cost GPS data.

In a given VSP mode, as speed increases, VSP becomes more sensitive to road grade. As will be shown in chapter 3, the desired (or target) precision required for road grade is ± 0.5 percent grade based on analysis of the sensitivity of VSP to road grade and speed.

This precision will lead to maximum misclassification of one VSP mode and does not produce a significant error in cycle average emission rates.

2.3 Methods for Measuring Road Grade

Various methods for estimating road grade include manual calculation of grade from design drawings, statistical estimation of grade using digital elevation maps, and on-board measurements with GPS receivers, sometimes in combination with altimeters, accelerometers, and inclinometers (Boriboonsomsin and Barth 2009; Rogers and Trayford 1984; Mangan et al. 2002; Zhang and Frey 2006).

Design drawings may be available for major road construction projects, such as a recently build interstate highways. Such drawings depict changes in elevation for segments of the road. Data from the drawings typically must be manually encoded. The as-built road might differ from the drawing because of changes during construction or subsequent modifications. Although vertical curvature is often indicated in design drawings, such as at the crest of a hill, drawings typically do not provide quantitative details. Design drawings are typically not available for many older or smaller roads. Zhang and Frey (2006) used design drawings for selected portions of I-40 and I-540 in the Raleigh, NC area as basis for comparison with other grade estimation methods.

Road grade can be inferred by instrumented vehicle measurements based on an accelerometer, which measures vehicle motion in three dimensions. The three dimensional acceleration vector provides insight regarding vehicle inclination and, hence, grade. Vehicle position can be estimated using dead reckoning based on odometer distance from

a known starting point, or using a GPS receiver for latitude and longitude. The precision depends on the vehicle selected and precision of individual instruments (Rogers and Trayford 1984). For example, the response of the vehicle suspension to imperfections of road surface can lead to random variations in accelerometer and inclinometer data (Mangan et al. 2002). Accelerometer drift bias which accumulates over time is another error source in accelerometer precision (Ogaja 2011).

Digital elevation maps represent a surface in three dimensions, usually in combination with orthophotos, which are geo-referenced photographs (Souleyrette et al. 2003; Mikhail et al. 2001; Brimicombe 2009). LIght Detection And Ranging (LIDAR) measurements made from an aircraft enable quantification of relative height based on the travel time for a LIDAR signal to return to the aircraft. The relative height is referenced to highly accurate measurements of actual altitude and location using other on-board instruments. Signal pulses can be made with horizontal spacing of centimeters over the surface terrain being measured, thus leading to highly detailed representations of changes in elevation of the surface (Brimicombe 2009). Although there are some surface features that can modify the signal return characteristics, for the most part LIDAR data provide clear representation of features such as buildings, streets, and other topography. LIDAR data are available only for limited locations. In North Carolina, LIDAR has been used for flood plain mapping. LIDAR data collected for flood plain mapping have been buffered to selected roads and used to estimate grade for selected routes. LIDAR-based estimates of road grade were found to agree well with design drawing-based estimates for selected interstate segments, while providing more realistic details regarding vertical curvature not captured by the design drawings (Zhang and Frey 2006).

Stand-alone GPS can record position and elevation, but are subject to significant errors that preclude direct use for road grade estimation. Errors include satellite-related, signal-related, and receiver-related biases and will be discussed in the next section. Availability of at least 4 satellites is required for GPS systems to calculate time and position. The accuracy of the position measurement is improved if the satellites are located at wide angles from each other, which reduces signal interference for horizontal positioning. However, elevation measurement is typically subject to more random error than the horizontal position measurements.

Differential GPS (DGPS) utilizes a base station at a known location to which the signal of a second GPS receiver, located in the vehicle, is compared. Since the base station and mobile receiver are both subject to many of the same measurement errors, comparison between them eliminates common errors and provides a more accurate estimate of position and elevation (Boriboonsomsin and Barth 2009). However, DGPS systems are generally significantly more expensive than stand-alone GPS receivers. As an example, a Trimble GeoXH 6,000 series DGPS costs about $15,000/each but the stand-alone Garmin 76CSx GPS receiver costs only about $250/each.

A barometer responds to changes in atmospheric pressure, and atmospheric pressure decreases with elevation. Weather patterns can cause variations in atmospheric pressure at a given elevation, but typically the rate at which pressure changes from such disturbance is relatively slow compared to the rate at which vehicle elevation is changing during driving. Furthermore, to compensate for run-to-run differences in barometric pressure associated with weather, the barometric altimeter can be calibrated to a known elevation at the start of each run. Barometric altimeters may provide useful data to characterize

changes in elevation more precisely than is possible with the GPS satellite signal data obtained from a stand-alone GPS receiver. Sahlholm et al. (2007) summarize a German patent application by Panzer (2003) in which GPS units with barometric altimeter are reported to produce more accurate estimates of elevation than obtainable from the GPS satellite signal data.

Because stand-alone GPS receivers with barometric altimeters are readily available at relatively low cost, this study focuses mostly on evaluating the accuracy of average measurements of road grade inferred from such instruments, and the repeatability of the measurements when comparing run-to-run variations. The Garmin 76CSx GPS receiver with in-built barometric altimeter is used (Garmin 2009). To enable measurement of a large sample size, three receivers are deployed simultaneously in each test vehicle for most of the runs reported here. However, for comparison purposes, four runs were done with a highly accurate Trimble GeoXH 6,000 series differential GPS.

2.4 GPS Instrumentation

A consumer grade Garmin 76CSx GPS receiver with in-built barometric altimeter (CGPS/BA) was used for most of the field measurements. The CGPS/BA has a position accuracy of ± 3 m. The accuracy of the elevation measured with the altimeter is ± 2 m on an absolute basis. Trimble GeoXH 6,000 serries DGPS position and elevation accuracy is about 10 cm; this system is capable of reporting the estimated horizontal and vertical accuracy on a second-by-second basis. This information is useful in quality assurance of GPS data where one can filter out inaccurate position and elevation data (based on

a defined acceptable threshold for error) before further processing them to acquire road grade. The filtered out seconds of data can then be replaced by a low cost CGPS/BA data to fill in the gaps.

All GPS receivers are subject to three general types of errors: (a) satellite-related biases; (b) signal propagation biases; and (c) receiver-related biases (Sickle 2008; Ogaja 2011).

Satellite-related biases consist of epherimis and clock errors. Epherimis errors occur when the satellite does not exactly follow its predicted orbital path and leads to errors of 1 to 6 meters in estimating location (Farrel 2008; Kaplan and Hegarty 2006). Satellite clock may deviate from the true time by 10^{-8} seconds which can lead to an error of about 3.5 meters (Ogaja 2011).

Signal propagation biases include atmospheric errors and multipath errors. Free electrons in the ionosphere and in lower layers of the atmosphere decrease signal propagation speed, leading to errors of between 2 to 5 meters. Multipath errors that occur when GPS signals are reflected by objects that are close to the receiver, such as buildings and tree canopies, lead to position errors of 0.1 to 3 meters (Ogaja 2011; Farrel 2008; Kaplan and Hegarty 2006).

Receiver-related biases depend on receiver properties and include receiver clock bias, and receiver noise. Deviation of the receiver clock from the true time can lead to a position error of up to 1 meter. Receiver noise is due to random errors take place in electronic pieces of the measurement equipment and can produce errors of up to 3 meters (Ogaja

2011).

Ephemeris errors, satellite clock errors and atmospheric errors are eliminated by differential correction; multipath errors can be reduced by using a multipath-resistant external antenna or using a receiver that is capable of filtering out multipath errors. Receiver-related errors cannot be removed by differential correction. Satellite-Based Augmentation Systems (SBAS) have improved the accuracy of consumer grade GPS by enabling them to use additional satellite-broadcast messages (Ogaja 2011; Wing 2009). In the U.S., SBAS is known as the Wide Area Augmentation System (WAAS). The reported position accuracy of consumer grade receivers that utilize WAAS is 7.6 meters or better, and depends also on the number of satellites from which signals are received (Wing 2009).

Another source of error in GPS-based measurements is that vehicle position is recorded at discrete intervals, typically every second. Since estimates of distance traveled between measurements are based on straight-line distances, there is the potential to underestimate the actual travel distance in comparison to the distance traveled on horizontally or vertically curved surfaces. Thus, the repeatability of estimated travel distances for selected routes are quantified.

2.5 Study Design and Field Data Collection

GPS data were collected at 1 Hz on four 2-way routes in Raleigh and Research Triangle Park area, NC as shown in Figure 2.3. Route selection was based upon an objective of having broad coverage of transportation network characteristics such as road grade and roadway classes. Fuel use and emissions regarding commuting trips connecting business

and residential centers are of interest for traffic managers and commuters. For example, commuters might like to choose the route with least fuel use and emissions. Traffic manager may want to optimize the traffic control strategy to reduce fuel use and emissions. Thus, data collection was designed to be conducted during commuting trips on selected routes connecting business and residential centers (Zhang 2006). Routes **A** and **C** are located between North Carolina State University (NCSU) and North Raleigh (NR), and Routes **1** and **3** are between North Raleigh (NR) and Research Triangle Park (RTP). Route **A**, with a roundtrip distance of 20.3 miles, is comprised entirely of arterials. The 22.5 miles roundtrip Route **C** includes 10.4 miles on freeways, with the balance on arterials. Route **1** includes 26.3 miles on freeways as part of the total roundtrip distance of 32.6 miles. In contrast, Route **3** is comprised of arterial roads for the entire 35.2 roundtrip distance. The 110.6 total miles of these routes includes roads ranging from two lane, two way minor arterials with speed limits of 25 mph to multilane freeways with speed limits of 65 mph. Three identical CGPS/BA receivers were used for data collection in each run. For comparison, four runs were done using a DGPS with VRS corrections in March 2012.

2.6 Data Analysis

This section is comprised of calculation of distance traveled and correction factor, individual runs approach, and combined runs approach.

2.6.1 Distance Traveled and Correction Factor

Horizontal distance traveled between two consecutive data points is calculated based on change in latitude and longitude from one second to the next using equidistant mapping

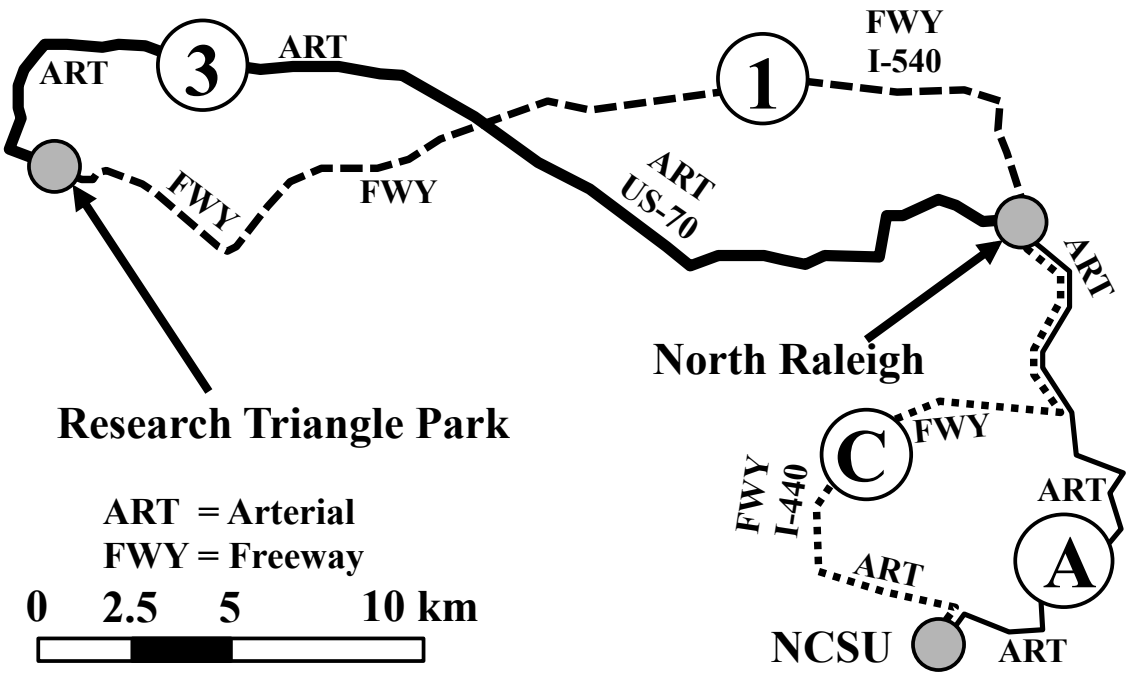


Figure 2.3: Study routes used for field data collection in Raleigh and RTP area, NC.

estimation (Grafarend and Krumm 2006):

$$D_{i,j} = \left(\frac{\pi}{180}\right) \mathrm{R} \sqrt{\left[(\phi_i - \phi_j)\right]^2 + \left[(\lambda_i - \lambda_j)\cos\left(\frac{\pi}{180}\left(\frac{\phi_i + \phi_j}{2}\right)\right)\right]^2} \tag{2.3}$$

where:

$D_{i,j}$ = Distance traveled between i^{th} and j^{th} second, (m)

ϕ_i = Latitude of i^{th} second, (decimal degree)

ϕ_j = Latitude of j^{th} second, (decimal degree)

λ_i = Longitude of i^{th} second, (decimal degree)

λ_j = Longitude of j^{th} second, (decimal degree)

R = Radius of the Earth, (6,371,009 m).

The cumulative distance at any point on the route is the summation of distance traveled per second for all previous seconds from the start of route. Because of GPS errors described earlier, the cumulative distance obtained from different runs can differ. Therefore, the total route length for each run is corrected to a "true" distance to allow for interpolation of position between the origin and destination on a consistent basis. The true distance is estimated based on the average of observed cumulative distances from approximately 100 runs with the CGPS/BA or 4 runs with DGPS. The distance correction factor for each run is the true distance divided by the observed distance. The corrected distance at any point along a route is (Zhang and Frey 2006):

$$d_{t,j} = c_f \left(\frac{d_{T,j}}{d_{M,j}} \right) \sum_{\text{Route } j} (s_{t,j} \Delta t) \tag{2.4}$$

where:

c_f = Conversion factor of 0.447, (m/s) per (mile/hr)

$d_{M,j}$ = Measured distance during one run along route j, (m)

$d_{t,j}$ = Corrected cumulative distance driven from the start of route j, (m)

$d_{T,j}$ = Reference "true" distance for route j, (m)

$s_{t,j}$ = Instantaneous vehicle speed at time t, (mile/hr)

Δt = Time elapsed between two consecutive data points, (s)

t = Arbitrary time, (s).

Because GPS receivers typically record data at 1 Hz, $\Delta t = 1$ sec.

The next two sections explain two different approaches for calculating road grade and precision form raw GPS data.

2.6.2 Individual Runs Approach

Typically GPS units record data at 1 Hz. The distance from one second to the next is calculated and accumulated to estimate the total distance from known coordinates at the origin and destination for each run. Measured elevations at each position along the route are binned into segments based on an averaging distance specified by the user, typically in the range of 0.08 km (0.05 mile) to 0.40 km (0.25 mile). The choice of segment length is based on comparison of the road grade profile from GPS data to LIDAR-based observations. As an example, for a portion of a route where LIDAR-based road grade varied within ±8 percent, 0.08 km (0.05 mile) segmentation resulted in variation of ±12 percent and 0.40 km (0.25 mile) segmentation led to variation of ±6 percent. However, 0.16 km (0.10 mile) segmentation resulted in variation of ±8 percent. Therefore, the 0.16 km segmentation gives the best estimate. More detailed comparison of the effect of different segmentation lengths on the road grade profile is illustrated in the results section. Linear regression is applied to data within each segment in each run to estimate the slope of the elevation versus distance, which is taken as the estimate of grade for that segment. Road grade is estimated for consecutive (non-overlapping) road segments. Average road grade is calculated for each segment among multiple individual runs.

In another method that is not explored here in detail, one can select segment length based on geometry and vertical curvature of a road. As an example, by looking at the elevation profile of a road, if the elevation versus cumulative distance is linear for a portion of a route that is longer than typical averaging distance, e.g. 0.16 km (0.10 mile), one can fit a linear regression model to the portion. At locations where vertical curvature because of peaks and valleys occur in the elevation profile, it is more realistic

to fit a second order polynomial function rather than a linear function. By looking at data and figuring out where peaks and valleys occur, second order polynomial can be fit to elevation profile. However, fitting a non-linear function will lead to non-constant grade within the portion, i.e. grade will change over distance within the portion. The disadvantage of this method is that defining a portion based on inspection of vertical curvature, leading to segments of varying lengths can be challenging. For example, in some routes there are multiple peaks and valleys right after each other; given that the GPS data logging frequency is 1 Hz, there might be only a few data points for the entire portion of the route that has those peaks and valleys. Thus, it may not be possible to fit a second order polynomial to each peak or valley due to lack of data.

Precision and Required Number of Runs

Average road grade and variability in estimated road grade is estimated for any location along the route, in user-specified segment lengths. Based on the desired coverage ($c_{\alpha,n}$) in terms of confidence level (α), sample size (n), and sample standard deviation (s), the confidence interval (CI) of the mean is estimated as:

$$CI = \pm c_{\alpha,n}\left(\frac{s}{\sqrt{n}}\right) . \tag{2.5}$$

For large sample sizes, the coverage for a 95 percent confidence interval is approximately 1.96. The sample size (n_{target}) that would be needed to achieve a desired precision (p) in the mean estimate of the road grade is estimated as:

$$n_{target} = \left(\frac{1.96s}{p}\right)^2 . \tag{2.6}$$

2.6.3 Combined Runs Approach

GPS data from multiple runs for each segment are combined. The mean grade and the precision of the road grade estimate are quantified using least squares regression estimators based on the combined runs. The method used here for analyzing GPS data for each route includes: (1) dividing the route into segments of length Δd; (2) aligning the average elevation among multiple GPS runs in each segment; (3) combining multiple runs into one data set; (4) calculating the average road grade for each segment; and (5) quantifying the precision of estimated raod grade.

For each run along a route, the 1 Hz GPS data are divided into segments of length Δd based on the corrected cumulative distance from a known origin. One GPS run is selected as a benchmark that is used as a reference, as indicated in Figure 2.4(a). For elevation measurements based on a barometric altimeter, there can be random variation in the absolute value of elevation associated with changes in area-wide atmospheric ambient barometric pressure. For purposes of estimating road grade, only relative changes in elevation are of interest. However, the statistical precision of the road grade estimates is influenced by random errors in absolute elevation. To reduce the effect of area-wide changes in atmospheric pressure on the analysis, the average elevation for each GPS run in each segment is calculated. The difference between the average elevation of each selected run versus the average elevation of the reference run is used to vertically shift all data points in the selected run, so that the average elevation of the run becomes the same as that of the reference run, as illustrated in Figures 2.4(a) and 2.4(b). This adjustment does not affect relative changes in elevation within the selected run, but enables all runs to be vertically aligned to the same average reference elevation within a run prior to

further analysis. As illustrated in Figure 2.4(c), multiple runs within each segment are combined into one data set, and linear regression is used to estimate the road grade. As indicated in the example, the road grade estimated based on the combined vertically aligned data is nearly the same (-5.4 percent versus -5.6 percent), but the estimated precision of 0.5 percent is much better than that of 1.9 percent based on the unadjusted vertical data.

Precision of Estimated Road Grade

Precision is the half width of 95% confidence interval on the estimated road grade. For each segment, a $100(1-\alpha)\%$ confidence interval on the estimated road grade is estimated as:

$$\left(\left(\frac{r}{100}\right) - t_{\left(\frac{\alpha}{2},n-2\right)}\sqrt{\frac{MSE}{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2}}, \left(\frac{r}{100}\right) + t_{\left(\frac{\alpha}{2},n-2\right)}\sqrt{\frac{MSE}{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2}}\right) \tag{2.7}$$

The precision of estimated road grade is:

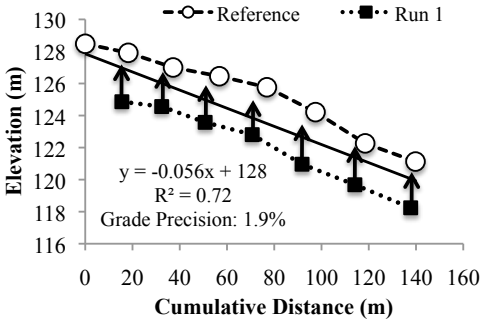
$$p = t_{\left(\frac{\alpha}{2},n-2\right)}\sqrt{\frac{MSE}{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2}} \tag{2.8}$$

Where:

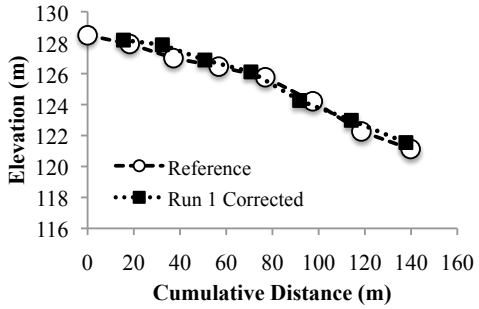
r	=	Estimated road grade for the segment, (percent)
MSE	=	Mean square error of the fitted line to the segment, (m^2)
n	=	Number of data points within the segment,
p	=	Precision of the estimated road grade for the segment, (fraction)
$t_{\left(\frac{\alpha}{2},n-2\right)}$	=	t-value with $\left(\frac{\alpha}{2}\right)$ level of significance and $(n-2)$ degrees of freedom,
x_i	=	Corrected cumulative distance at point i within the segment, (m)
$\bar{x}$	=	Average of corrected cumulative distances within the segment, (m).

For a 95% confidence interval, α=0.05. For large values of n (n > 30), $t_{\left(\frac{\alpha}{2},n-2\right)}$ is approximately 1.96. Therefore, if a sufficiently large number of GPS runs are combined together such that each segment is comprised of more than 30 data points, Equation 2.8 can be simplified as:

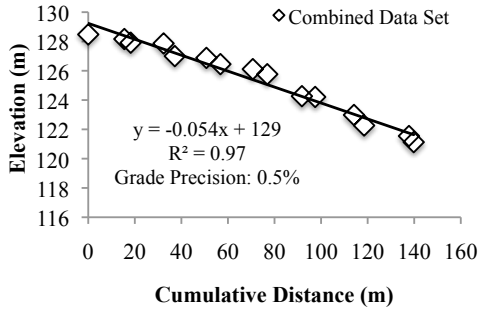
$$p = 1.96\sqrt{\frac{MSE}{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2}} \tag{2.9}$$



(a)



(b)



(c)

Figure 2.4: Schematic of vertical alignment procedure in for a segment of road: (a) raw elevation versus distance within a segment for a reference and selected run; (b) adjustment of the selected run to the same average elevation as the reference run; (c) estimation of road grade for the combined runs using linear regression.

Chapter 3

Results

This chapter shows the followings: sensitivity analysis of vehicle specific power with respect to road grade, sensitivity of cycle average vehicle fuel use and emissions to road grade, repeatability of measured distances, individual runs approach results, combined runs approach results, and differential GPS results.

3.1 Sensitivity Analysis of Vehicle Specific Power with Respect to Road Grade

The sensitivity of VSP to road grade is illustrated in Figure 3.1. For a flat road (0 percent grade), VSP increases from approximately 2 kW/ton to 16 kW/ton (ranging from VSP mode 3 to 8) as vehicle speed increases from 30 km/hr to 120 km/hr. In contrast, for a road with +6 percent grade, VSP increases from mode 5 to mode 13 for the same variation in speed. Thus, as grade increases, VSP becomes more sensitive to grade. At a relatively low speed of 30 km/hr, road grade within a VSP bin can vary by as much as 3.6 percentage points. For example, at 30 km/hr, road grade between -0.3 to $+3.3$ percent

produces VSP values between 1 to 4 kW/ton, and thus are contained within VSP mode 4. This implies that a variation in road grade of approximately ±1.8 percentage points would lead to a similar estimate of VSP mode, or might lead to misclassification by just one adjacent mode (e.g., mode 3 or mode 5). The fuel use and emission rates of modes 3 through 5 are typically statistically different from each other, but are typically small compared to the cycle average emission rates. Thus, a misclassification by one mode would not produce a substantial error in cycle average emission rates.

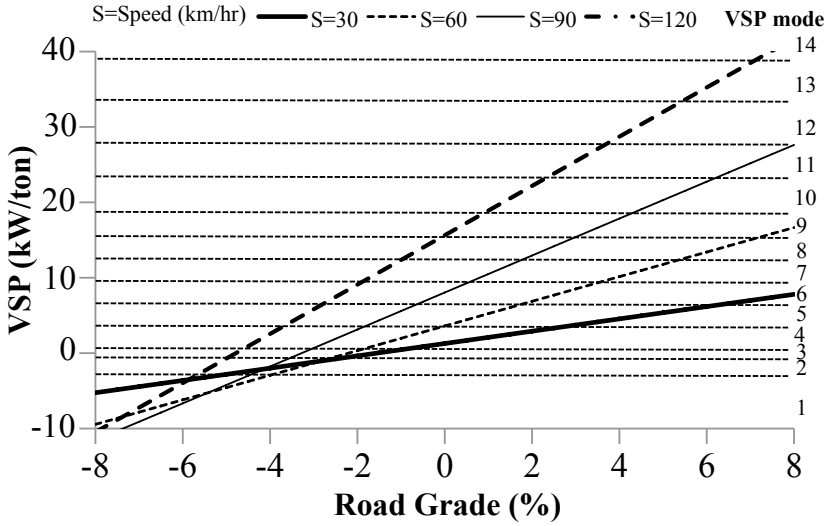


Figure 3.1: Sensitivity of Vehicle Specific Power (VSP) to Road Grade and Speed. Horizontal dashed lines separate VSP modes. Acceleration is zero.

As speed increases, the value of VSP and the classification into a mode becomes more sensitive to road grade. At 120 km/hr, the range of road grades within modes 4 through 9 is 0.92 percentage points. For example, for mode 6, road grade must be between −2.64 and −1.72 percent at this speed. The desired precision of the road grade estimate is

inferred to be ±0.45 percentage points based on this relatively high speed. However, for typical speeds of most urban driving, such as 90 km/hr or lower, an acceptable precision is approximately ±0.6 percent. As a nominal value, we adopt ±0.5 percentage points as a desired target precision for road grade estimates.

3.2 Repeatability of Measured Distances

CGPS/BA-based measurements of distance driven on each route were highly repeatable, as illustrated in Figure 3.2 for Route 3O. This route is 28.53 km (17.73 miles) long based on the average of 89 CGPS/BA runs, which is closely comparable to distance estimated using GIS. Approximately 85 percent of the runs are within approximately ±0.5 percent of the average distance, or an error of less than 0.16 km (0.10 mile). There are 5 runs for which the estimated difference was one percent or more less than the average distance. Of these, 3 appear to be associated with intermittent loss of GPS signal on horizontally curved roads, leading to underestimation of distance. The remaining runs appear to be associated with paths on multi-lane roads that have shorter distances than the typical path. The example shown is typical of those for the other seven one-way routes analyzed. In addition, the four DGPS runs on Route 3O, as well as other 7 routes, show very high repeatability in traveled distances; the observed ones for Route 3O are all 17.61 miles and hence the distance correction factor is 1.00 for them.

3.3 Individual Runs Approach Results

Sensitivity of average road grade to averaging distance, run-to-run variability and confidence interval for mean road grade, estimated sample size to achieve a target precision

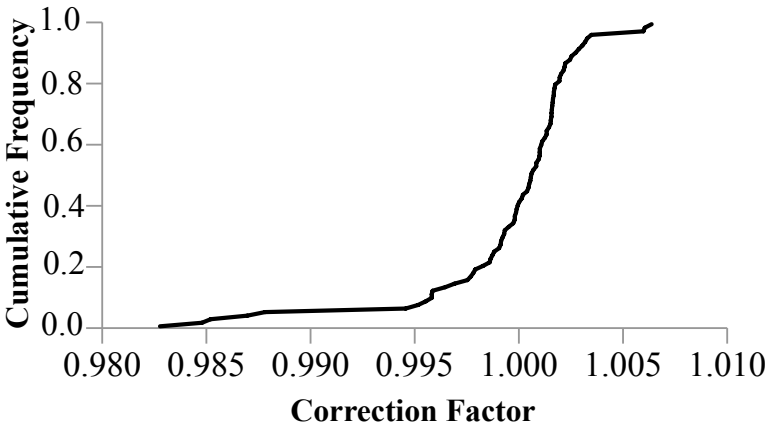


Figure 3.2: Cumulative Frequency Distribution of Correction Factors for Route 3O, True Route Length: 28.53 km, n = 89.

of road grade, variation in target sample size with respect to road grade magnitude, and benchmark comparisons to LIDAR-based road grade are presented in this section.

3.3.1 Sensitivity of Average Road Grade to Averaging Distance

Estimates of road grade are sensitive to the averaging distance used, as illustrated for the example of Route CO in Figure 3.3. For the shortest averaging distance considered of 0.08 km, estimated road grade ranges from −10 percent to +6 percent. As the averaging distance increases, the variability in estimated grade decreases. For example, for 0.16 km averaging, the estimated grades range from −7 percent to +5 percent, whereas the range is only −4 percent to +3 percent for 0.40 km averaging. The estimated variability in grade decreases as the averaging distance increases. The choice of averaging distance represents a trade-off between too much random noise, if the averaging distance is too short, versus underestimation of actual vertical slopes on the road, if the averaging distance is too long. Short averaging segments can potentially be based on very few GPS measurements,

leading to substantial random variability. For instance, for a vehicle traveling 50 km/hr, there would be only 6 data points per 0.08 km segment, versus double that for a 0.16 km segment. An averaging distance of 0.16 km is used throughout the rest of this paper to avoid too much random error associated with small sample sizes while retaining details regarding changes in slope of the road.

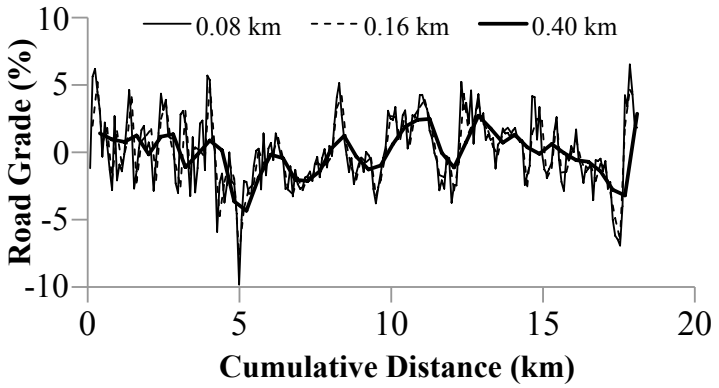


Figure 3.3: Comparison of the calculated average road grade for 0.08, 0.16, 0.40 km (0.05, 0.10, 0.25 mile) segmentations of Route CO; this graph is based on one run.

3.3.2 Run-to-Run Variability and Confidence Intervals for Mean Road Grade

The repeatability of road grade estimates is discussed here for Route 3O. The average grade, based on 89 runs, varies by approximately ±6 percent in the North Raleigh portion of the route, but only by ±2 percent in the Research Triangle Park portion. The standard deviation of the road grade is typically approximately 1 percentage point or less for each 0.16 km segment, which indicates substantial run-to-run variability.

The confidence interval on the mean estimate of road grade for Route 3O, as shown in Figure 3.4, is approximately ±0.1 percentage points for most 0.16 km segments, at a sample size of n = 89. Thus, it is possible to obtain a precise estimate of the mean grade with a large number of repeated runs. This result is typical for all routes. A change in road grade of only 0.1 percent or 0.2 percent does not typically lead to a large difference in estimated fuel use or emission rate; thus, this level of precision would typically be more than adequate for use in combination with VSP-based modal emission models.

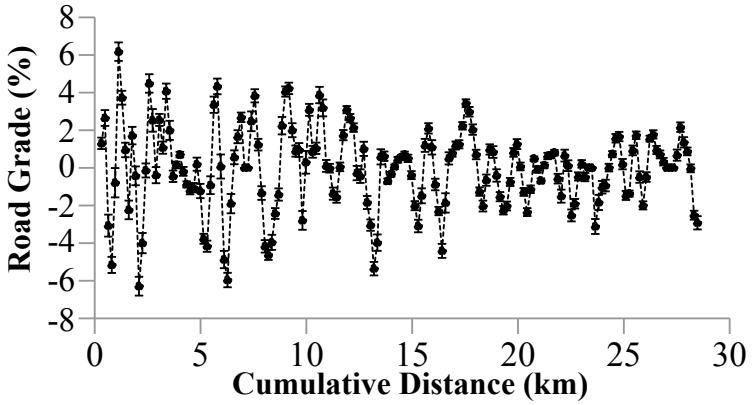


Figure 3.4: Average road grade with 95 percent confidence intervals on the average for Route 3O based on 0.16 km segmentation, n = 89.

3.3.3 Estimated Sample Size to Achieve a Target Precision of Road Grade

Cumulative distribution functions of the minimum required sample size to obtain a desired road grade precision for each of the 1116 of 0.16 km segments on all of the measured routes are shown in Figure 3.5. The minimum required sample size is estimated based

on Equation 2.6 for each segment. To achieve ±0.5 percent precision requires a sample size of 4 to 86, based on a 95% frequency range across all 1116 segments, with a median of 14 and a mean of 22. These sample sizes are feasible as part of cross-sectional studies involving many vehicles. Furthermore, if three CGPS/BA receivers are used simultaneously, then the actual number of vehicle runs needed is only seven on average and about four for the median. The number of vehicle runs needed can be reduced by using more inexpensive CGPS/BA receivers. Even ten such receivers are significantly cheaper than a DGPS. If a sample size of 100 is obtained, similar to the amount of data obtained here, there is very high confidence that nearly all 0.16 km segments will have road grade estimates precise to within ±0.5 percent, with approximately 70 percent of the segments having precision of ±0.25 percent or better, and approximately 2 percent having precision of ±0.1 percent or better.

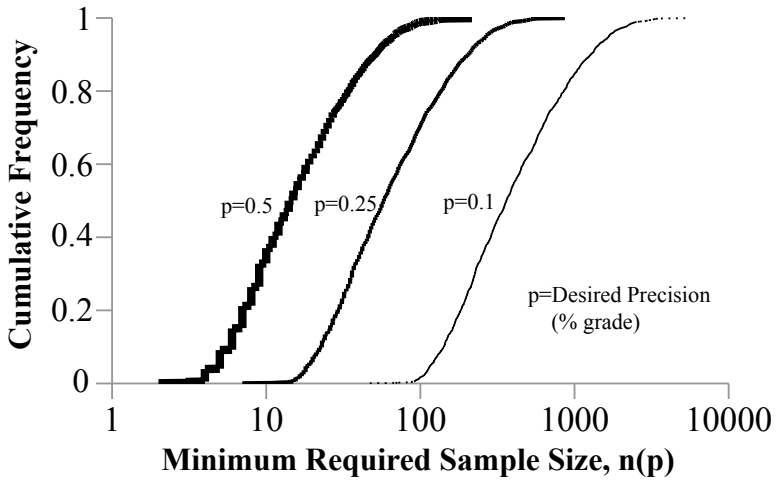


Figure 3.5: Cumulative Frequency Distributions of estimated required sample size, for 3 precision targets of ±0.1, ±0.25, and ±0.5 percent based on 0.16 km segmentation of all 8 routes.

3.3.4 Variation in Target Sample Size with Respect to Magnitude of Road Grade

The average required sample size to obtain a desired road grade precision is a weak function of road grade, as illustrated in Figure 3.6 based on data from all 1116 segments for all measured routes. The horizontal axis is the average road grade for every 0.16 km segment and the vertical axis is the corresponding minimum required sample size estimated based on Equation 2.6 for each segment. For a desired precision of ± 0.5 percent grade, an average of approximately 20 samples are needed at zero percent grade, increasing to over 50 for -6 percent or $+6$ percent grade. There are only twelve 0.16 km segments (out of over 1116 segments) for which sample sizes of over 100 are needed. Thus, as expected, the sample size to achieve a desired precision tends to increase as the magnitude of the grade increases. However, there is also substantial variability in the required sample size that is not explained by differences in road grade, as indicated by the low coefficient of determination of only 0.077.

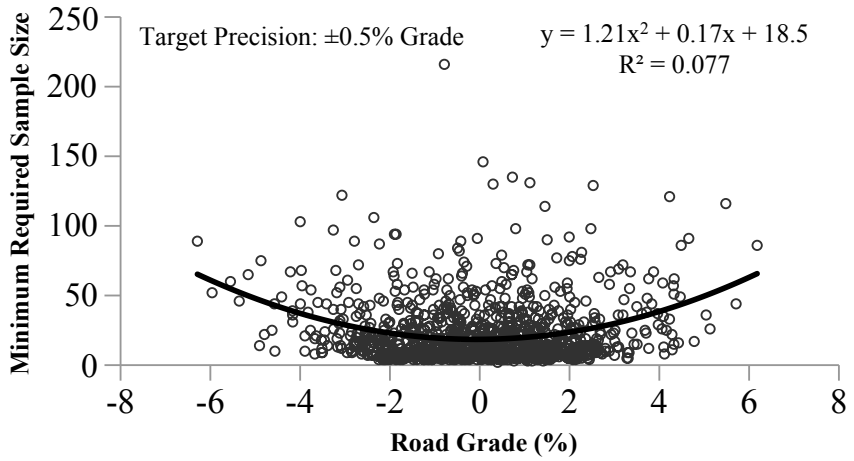


Figure 3.6: Estimated required sample size for ±0.5 percent precision versus road grade based on the 0.16 km segmentation of all 8 routes.

3.3.5 Benchmark Comparison to LIDAR-Based Road Grade

LIDAR-based road grade profiles are the best available estimates for the routes explored here and are representative of the true road grade. Zhang and Frey (2006) showed that LIDAR-based road grade is in agreement with highway design drawing data that includes portions of the routes studied here. LIDAR-based road grade presented here is based on defining segments on the road according to geometry and vertical curvature of the road. The use of LIDAR data to estimate road grade involves fitting a plane to digital elevation data for segments of roadways using bivariate linear regression techniques. Distances for LIDAR points falling within the defined road segment from and along the centerline of the road segment were calculated based upon an assumed local origin. Finally, calculated distances were used for regression to estimate road grade. Therefore, segment length is

not constant among different segments; in Routes AO, 1O, 1I, AI, CO, 3O, 3I, and CI, 90% , 65% , 65% , 88% , 81% , 82% , 79% , and 81% of segment lengths are smaller than 0.10 mile, respectively. For comparison purposes with GPS, LIDAR-based road grade values are linearly interpolated between the two adjacent points to every 0.10 mile and the interpolated value is assumed to be the road grade for the segment. As an alternative, one can use distance-based weighted average to standardize LIDAR road grade for every 0.10 mile segment. Range of variability in road grade estimates can be illustrated by R^2 of regression fit; low R^2 values indicate high variability in road grade estimate. Table 3.1 shows a summary of segment length and coefficient of determination for some portions of I-540 and I-40 for LIDAR-based road grade (Zhang 2006). The maximum and minimum ranges of variability occur in segments with grades less than 0.5 percent and more than 1.0 percent, respectively.

Table 3.1: Summary of Segment Length and Coefficient of Determination, R^2, of Bivariate Linear Regression for LIDAR-Based Road Grade Estimates for Portions of I-540 and I-40, in RTP Area, NC. $|\mathbf{G}|$ is Road Grade Magnitude (Zhang 2006).

Highway	**Mean Segment Length (mi)**	**R^2 Range ($|\mathbf{G}| < 0.5\%$)**	**R^2 Range ($0.5\% \leq |\mathbf{G}| \leq 1.0\%$)**	**R^2 Range ($1.0\% < |\mathbf{G}|$)**
I-540	0.18	$0.19 - 0.99$	$0.86 - 0.99$	$0.98 - 0.99$
I-40	0.16	$0.19 - 0.94$	$0.69 - 0.99$	$0.93 - 0.99$

Note: For I-540, the median R^2 are 0.55, 0.95 and 0.99 for the three road grade classes in ascending order, respectively. The maximum and minimum segment lengths are 0.96 and 0.02 mile, respectively. For I-40, the median R^2 are 0.71, 0.95 and 0.99 for the three road grade classes in ascending order, respectively. The maximum and minimum segment lengths are 0.88 and 0.03 mile, respectively.

The accuracy of the measured road grade is evaluated by comparison to LIDAR data, as illustrated in Figure 3.7 for Route 3O. For example, at a distance of approximately 4.8 km from North Raleigh, the average road grade is -4 percent, which compares to a similar value from the LIDAR data. A few tenths of a kilometer down the road, the grade increases to $+4$ percent based on the average GPS data, compared to approximately $+5$ percent from the LIDAR data. At approximately 6.4 km cumulative distance, the grade decreases to approximately -6 percent based on the GPS and LIDAR data, and then increases to approximately $+4$ percent at a cumulative distance of 8 km for both types of data. While it is clear that there is not exact agreement between the average GPS data and the LIDAR data, there is substantial concordance between the data. For example, most of the peaks for both positive and negative grades occur relatively at the same cu-

mulative distances for both average GPS and LIDAR data. The choice of segment length in LIDAR-based method can affect the horizontal synchronization of LIDAR compared to GPS-based road grade profile. While it has been tried to horizontally align LIDAR and GPS data together by shifting the profiles, there are still some parts that the locations of peaks and valleys do not match between LIDAR and GPS. Some parts have better synchronization and some have worse. For example in Figure 3.7, if one looks at two road grade profiles, from cumulutive distance of zero to about 13 km both of them are horizontally aligned and peaks and valleys occur at the same locations; however, from about 13 km to 24 km there is a shift of about 0.10 km between two profiles and same peaks and valleys occur at about 0.10 km of each other in the two profiles. While the LIDAR data are a useful benchmark, they do not necessarily represent ground-level truth in all cases. For example, the sharp changes in road grade shown at a cumulative distance of approximately 13 km are not evident from inspection of the site. At 17 km, the LIDAR data indicate a sharp change in grade from -6 percent to $+2$ percent in just about one tenth of a kilometer, compared to a more gradual change from -4 percent to $+1$ percent as implied by the average GPS data. The latter is more realistic.

Results for other routes are qualitatively similar, with the exception of portions of Routes **A** and **C**. The intersection of Hillsborough Street and Pullen Road has been reconstructed, leading to differences between LIDAR data obtained prior to the construction versus average GPS data from after the construction. Overall, the comparison indicates that the average GPS data captures road grade features consistent with the LIDAR data, while being somewhat less extreme in terms of characterizing large changes in very short distances that are physically unrealistic.

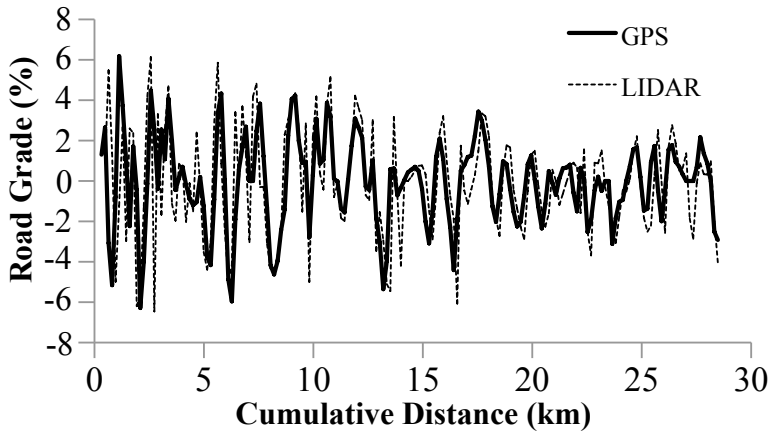


Figure 3.7: Comparison of GPS with LIDAR road grade for Route 3O based on 0.16 km segmentation.

3.4 Sensitivity of Cycle Average Vehicle Fuel Use and Emissions to Road Grade

Vehicle specific power modal distribution depends on road grade. Using the example of VSP-based modal fuel use and emission rates for a 2011 Chevrolet HHR as given in Figure 2.2, and based on all study routes as shown in Figure 2.3, the effect of road grade (average of 100 runs) on cycle average rates is quantified in Table 3.2. For the portions of the routes with negative grade, the fuel use rate is overestimated by 10 percent and the emission rates are overestimated by 13 to 26 percent, depending on the pollutant, if road grade is not taken into account. Conversely, for portions of the route with positive grade, the fuel use rate is underestimated by 12 percent and the emission rates are underestimated by 21 to 46 percent, depending on the pollutant. Since the trend in fuel use rate versus positive VSP is approximately linear, positive and negative grades approximately offset each other, leading to a net bias in overall average fuel use

rate of only −2 percent. However, because the trends in emission rates are nonlinear with respect to positive VSP, the overall bias in emission rates is much higher, at −7 to −14 percent depending on the pollutant. Thus, if road grade is not taken into account, there can be substantial misestimation of localized emissions that affect near-roadway air quality and human exposure to pollutants, and of area-wide estimates that affect urban and regional scale air quality and exposure.

Table 3.2: The Percent Differences in Fuel Use and Emission Rates Based on Zero Road Grade versus Actual Road Grade (Average of 100 Runs) and Modal Analysis of a 2011 Chevrolet HHR for All Study Routes

Portion	**Fuel Use**	**NO_x**	**HC**	**CO**
With Negative Grade	10	18	13	26
With Positive Grade	−12	−46	−21	−35
All Routes	−2	−14	−7	−9

In another case study, VSP modal results of three cases are presented for a 2011 Ford F-150XL: (1) using average road grade of 100 GPS runs to calculate VSP, (2) using 1 GPS run to calculate road grade and VSP, and (3) ignoring road grade term in VSP equation. Comparison between Cases 2 versus 1 and Cases 3 versus 1 are made. Results are shown in Tables 3.3 and 3.4, respectively. If using only one GPS run to calculate road grade, fuel use error in VSP modal rates varies between −4.79 to 2.77 percent compared to using average road grade from 100 runs; errors in emission rates in the VSP modal analysis vary between −31.80 to 25.16 depending on the mode and pollutant. Average cycle mass of fuel consumed and pollutants emitted is calculated based on the distribution

of second-by-second VSP values in the 14 VSP modes. It is the sum of products of time spent in each VSP mode and average fuel use or emission rates. For comparison purposes, it is assumed that the "correct" time-based distribution of VSP is the one obtained from using average road grade of 100 runs. Multiplying the "correct" time distribution by average fuel use and emission rates and summing them over the 14 VSP modes will give the mass of fuel consumed and pollutants emitted. Average cycle differences are −1.6, −1.4, −1.5, −6.2, and −1.6 percent for fuel use, NO_x, HC, CO, and CO_2, respectively. If ignoring the road grade, fuel use error in VSP modal rates varies between −11.49 to 17.50 percent; emission rates error in VSP modal analysis varies between −47.72 to 186.2 percent depending on the mode and pollutant. Again for comparison purposes, it is assumed that the "correct" time-based distribution of VSP is the one obtained from using average road grade of 100 runs. Multiplying the "correct" time distribution by average fuel use and emission rates and summing them over the 14 VSP modes will give the mass of fuel consumed and pollutants emitted; average cycle differences are 0.1, −0.7, −0.3, 1.1, and 0.1 percent for fuel use, NO_x, HC, CO, and CO_2, respectively. The reason that average cycle differences in both cases are relatively small is that over the entire trip positive and negative road grade tend to cancel out each other's effect and thus road grade does not have a significant influence on the entire trip fuel use and emissions; however, at any specific location, fuel use and emissions are sensitive to road grade. By looking at the percent differences in each case, it is inferred that variability in NO_x and CO emission rates is higher than other pollutants; this is expected as these two pollutants are more sensitive to change in engine load.

Table 3.3: Comparison of Using Average Road Grade Obtained from 100 GPS Runs versus Using Only One GPS Run Road Grade in VSP Modal Analysis of Fuel Use and Emission Rates for a 2011 Ford F-150XL

	VSP Mode	VSP Range (kW/ton)	Sample Size	Fuel Use (g/s)	NO_x (mg/s)	HC (mg/s)	CO (mg/s)	CO_2 (g/s)
Road Grade Obtained from Average of About 100 GPS Runs	1	Below −2	2,451	0.68	0.15	1.57	3.00	2.04
	2	−2 – 0	557	0.82	0.17	1.59	1.69	2.48
	3	0 – 1	3,500	0.40	0.03	0.65	1.13	1.23
	4	1 – 4	778	1.35	0.19	2.39	3.53	4.08
	5	4 – 7	791	1.81	0.24	3.16	3.95	5.49
	6	7 – 10	785	2.22	0.26	3.88	6.63	6.71
	7	10 – 13	693	2.58	0.37	4.46	6.74	7.82
	8	13 – 16	670	3.02	0.35	5.09	7.97	9.14
	9	16 – 19	530	3.33	0.42	5.85	10.03	10.07
	10	19 – 23	528	3.90	0.52	6.88	13.86	11.81
	11	23 – 28	461	4.36	0.56	7.65	14.81	13.21
	12	28 – 33	286	4.88	0.49	8.18	16.11	14.79
	13	33 – 39	210	5.61	0.55	9.53	38.96	16.96
	14	Over 39	135	7.28	1.11	12.03	117.4	21.90
Only One GPS Run Road Grade	1	Below −2	2,509	0.67	0.15	1.51	2.98	2.03
	2	−2 – 0	597	0.84	0.15	1.63	2.03	2.55
	3	0 – 1	3,449	0.39	0.02	0.64	1.10	1.17
	4	1 – 4	762	1.38	0.20	2.53	3.58	4.19
	5	4 – 7	791	1.83	0.25	3.17	4.94	5.54
	6	7 – 10	729	2.13	0.23	3.69	4.56	6.45
	7	10 – 13	624	2.62	0.40	4.66	8.10	7.93
	8	13 – 16	629	2.91	0.36	4.90	8.37	8.80
	9	16 – 19	569	3.36	0.40	5.95	9.03	10.16
	10	19 – 23	522	3.72	0.50	6.48	9.46	11.28
	11	23 – 28	448	4.31	0.57	7.71	17.93	13.05
	12	28 – 33	328	4.77	0.53	7.87	16.21	14.44
	13	33 – 39	230	5.49	0.58	9.25	39.67	16.60
	14	Over 39	187	7.01	0.94	11.38	86.32	21.14
Percent Difference Between Only One GPS Run versus Average of About 100 GPS Runs	1	Below −2	2.37	−0.88	−3.33	−3.51	−0.83	−0.88
	2	−2 – 0	7.18	2.66	−7.83	2.64	19.79	2.64
	3	0 – 1	−1.46	−4.79	−7.69	−2.45	−2.65	−4.79
	4	1 – 4	−2.06	2.77	6.88	5.77	1.36	2.77
	5	4 – 7	0.00	1.00	3.35	0.16	25.16	0.98
	6	7 – 10	−7.13	−3.97	−12.93	−4.79	−31.21	−3.93
	7	10 – 13	−9.96	1.50	6.17	4.42	20.23	1.47
	8	13 – 16	−6.12	−3.71	1.14	−3.62	5.03	−3.72
	9	16 – 19	7.36	0.90	−4.27	1.86	−10.05	0.91
	10	19 – 23	−1.14	−4.52	−4.25	−5.83	−31.80	−4.47
	11	23 – 28	−2.82	−1.15	2.32	0.76	21.09	−1.19
	12	28 – 33	14.69	−2.40	7.76	−3.78	0.58	−2.40
	13	33 – 39	9.52	−2.14	5.63	−2.92	1.80	−2.15
	14	Over 39	38.52	−3.67	−15.20	−5.42	−26.46	−3.48

Table 3.4: Comparison of Using Average Road Grade Obtained from 100 GPS Runs versus Ignoring Road Grade in VSP Modal Analysis of Fuel Use and Emission Rates for a 2011 Ford F-150XL

	VSP Mode	VSP Range (kW/ton)	Sample Size	Fuel Use (g/s)	NO_x (mg/s)	HC (mg/s)	CO (mg/s)	CO_2 (g/s)
Road Grade Obtained from Average of About 100 GPS Runs	1	Below −2	2,451	0.68	0.15	1.57	3.00	2.04
	2	−2 – 0	557	0.82	0.17	1.59	1.69	2.48
	3	0 – 1	3,500	0.40	0.03	0.65	1.13	1.23
	4	1 – 4	778	1.35	0.19	2.39	3.53	4.08
	5	4 – 7	791	1.81	0.24	3.16	3.95	5.49
	6	7 – 10	785	2.22	0.26	3.88	6.63	6.71
	7	10 – 13	693	2.58	0.37	4.46	6.74	7.82
	8	13 – 16	670	3.02	0.35	5.09	7.97	9.14
	9	16 – 19	530	3.33	0.42	5.85	10.03	10.07
	10	19 – 23	528	3.90	0.52	6.88	13.86	11.81
	11	23 – 28	461	4.36	0.56	7.65	14.81	13.21
	12	28 – 33	286	4.88	0.49	8.18	16.11	14.79
	13	33 – 39	210	5.61	0.55	9.53	38.96	16.96
	14	Over 39	135	7.28	1.11	12.03	117.4	21.90
Ignoring Road Grade	1	Below −2	2,666	0.79	0.15	1.74	2.99	2.40
	2	−2 – 0	308	0.86	0.13	1.24	4.85	2.61
	3	0 – 1	3,374	0.36	0.02	0.56	0.99	1.09
	4	1 – 4	762	1.35	0.17	2.30	3.14	4.10
	5	4 – 7	1,074	1.89	0.26	3.42	3.77	5.71
	6	7 – 10	684	2.25	0.24	3.99	4.02	6.83
	7	10 – 13	817	2.71	0.35	5.10	6.34	8.22
	8	13 – 16	703	3.12	0.43	5.10	13.02	9.43
	9	16 – 19	490	3.13	0.49	5.31	10.05	9.47
	10	19 – 23	468	3.66	0.47	6.59	8.35	11.09
	11	23 – 28	388	4.25	0.57	7.97	12.03	12.88
	12	28 – 33	365	4.83	0.61	7.72	30.09	14.60
	13	33 – 39	151	5.46	0.44	8.95	20.37	16.52
	14	Over 39	125	7.00	1.14	11.01	140.6	21.00
Percent Difference Between Ignoring Road Grade versus Using Average of About 100 GPS Runs	1	Below −2	8.77	17.50	−1.33	11.10	−0.57	17.55
	2	−2 – 0	−44.70	5.17	−24.10	−22.17	186.2	5.00
	3	0 – 1	−3.60	−11.49	−38.46	−14.09	−12.57	−11.49
	4	1 – 4	−2.06	0.42	−7.94	−3.89	−11.08	0.44
	5	4 – 7	35.78	4.08	8.37	8.16	−4.41	4.08
	6	7 – 10	−12.87	1.72	−10.65	2.78	−39.44	1.78
	7	10 – 13	17.89	5.16	−6.43	14.37	−5.85	5.17
	8	13 – 16	4.93	3.23	21.65	0.20	63.42	3.15
	9	16 – 19	−7.55	−5.99	14.93	−9.14	0.12	−6.00
	10	19 – 23	−11.36	−6.16	−9.07	−4.27	−39.81	−6.10
	11	23 – 28	−15.84	−2.53	1.60	4.21	−18.76	−2.51
	12	28 – 33	27.62	−1.12	23.88	−5.65	86.76	−1.26
	13	33 – 39	−28.10	−2.80	−20.69	−6.05	−47.72	−2.63
	14	Over 39	−7.41	−3.90	2.70	−8.48	19.74	−4.09

3.5 Proper Synchronization of Average Road Grade with PEMS and OBD Data

Proper synchronization of average road grade with PEMS and OBD data is critical. To achieve this, GPS data obtained from the test day should be first synchronized with OBD data based on speed profile. Average road grade is available for every 0.10 mile segment of each of the 8 Routes. Thus, starting from the beginning point of each route, one should assign the average road grade to the corresponding seconds of data associated with each 0.10 mile. After assigning the average road grade to all seconds of data, it is important to check the proper synchronization of average road grade with the observed test day road grade data for every 0.10 mile. To do this, using the SyncUtility package of PEMS Quality Assurance Software (PQAS), one should plot the time series of average road grade and observed test day road grade together and check the trends of road grade change and correlation between them. If the trends look similar, the synchronization has been done correctly. Otherwise, data should be re-visited and possible sources of error such as wrong turns should be double-checked. To illustrate the importance of proper synchronization of road grade with PEMS and OBD data, a case study is done on a 2011 Chevrolet HHR, Table 3.5. Based on properly synchronized data, a monotonic increase in fuel use versus positive VSP modes (modes 3 through 14) is expected. In the second scenario, road grade is mis-aligned for 30 seconds compared to PEMS and OBD data; if the vehicle is driven at 45 (mph) on average, 30 seconds is about 0.40 miles. VSP modal analysis shows that fuel use increases monotonically with positive VSP modes 3 to 13 but not in mode 14 in the latter case where road grade is not properly synchronized. Moreover, the difference in fuel use in VSP modal analysis between well- and poorly-synchronized ranges between -19.79 to 31.21 percent for individual modes; the difference in individual modal estimates

among all modes and pollutants ranges from −48.09 to 225.0 percent depending on the mode and the pollutant. For comparison purposes, it is assumed that the "correct" time-based distribution of VSP is the one obtained from using the well-synchronized data. Multiplying the "correct" time distribution by average fuel use and emission rates and summing them over the 14 VSP modes will give the mass of fuel consumed and pollutants emitted; average cycle differences between well- and poorly-synchronized modal analysis are −0.5, −0.5, −0.8, −1.2, and −0.5 percent for fuel use, NO_x, HC, CO, and CO_2, respectively. The reason that average cycle differences are relatively small is that over the entire trip positive and negative road grade tend to cancel out each other's effect and thus road grade does not have a significant influence on the entire trip fuel use and emissions; however, at any specific location, fuel use and emissions are sensitive to road grade and proper synchronization of road grade with PEMS and OBD data is important.

Table 3.5: Comparison of VSP Modal Fuel Use and Emission Rates Between Well-Synchronized and Poorly-Synchronized Road Grade with PEMS and OBD Data for a 2011 Chevrolet HHR. Average Road Grade from 100 Runs is Used.

	VSP Mode	VSP Range (kW/ton)	Sample Size	Fuel Use (g/s)	NO_x (mg/s)	HC (mg/s)	CO (mg/s)	CO_2 (g/s)
Well-Synchronized Road Grade with PEMS and OBD Data	1	Below −2	2,206	0.39	0.01	0.03	5.13	1.22
	2	−2 – 0	830	0.49	0.01	0.05	6.73	1.56
	3	0 – 1	5,563	0.30	0.00	0.02	1.67	0.96
	4	1 – 4	1,339	0.75	0.02	0.06	11.35	2.37
	5	4 – 7	999	1.11	0.04	0.09	12.96	3.50
	6	7 – 10	995	1.44	0.07	0.10	17.00	4.53
	7	10 – 13	848	1.77	0.10	0.12	19.06	5.58
	8	13 – 16	704	2.01	0.15	0.13	20.30	6.34
	9	16 – 19	569	2.30	0.22	0.17	27.32	7.25
	10	19 – 23	541	2.60	0.35	0.17	43.42	8.17
	11	23 – 28	363	2.90	0.50	0.16	24.72	9.14
	12	28 – 33	189	3.10	0.75	0.19	54.23	9.75
	13	33 – 39	110	3.24	0.93	0.31	127.9	10.05
	14	Over 39	45	3.69	1.26	0.34	189.0	11.41
Poorly-Synchronized Road Grade with PEMS and OBD Data	1	Below −2	2,261	0.51	0.02	0.04	5.77	1.60
	2	−2 – 0	810	0.60	0.03	0.05	7.10	1.90
	3	0 – 1	5,467	0.31	0.00	0.02	1.74	0.97
	4	1 – 4	1,293	0.85	0.04	0.07	11.77	2.68
	5	4 – 7	1,085	1.15	0.05	0.09	13.15	3.61
	6	7 – 10	920	1.47	0.09	0.12	17.98	4.63
	7	10 – 13	918	1.71	0.10	0.11	16.94	5.38
	8	13 – 16	688	1.92	0.14	0.11	21.34	6.04
	9	16 – 19	564	2.03	0.21	0.14	32.61	6.37
	10	19 – 23	551	2.35	0.29	0.13	28.89	7.40
	11	23 – 28	355	2.55	0.53	0.21	54.90	7.98
	12	28 – 33	190	2.85	0.67	0.17	38.08	8.95
	13	33 – 39	107	3.07	0.71	0.16	67.30	9.62
	14	Over 39	61	2.96	0.65	0.29	159.8	9.14
Percent Difference	1	Below −2	2.49	31.21	72.73	39.29	12.35	31.34
	2	−2 – 0	−2.41	21.95	225.0	11.11	5.53	22.07
	3	0 – 1	−1.73	1.43	0.00	0.00	4.14	1.42
	4	1 – 4	−3.44	12.71	84.21	15.52	3.73	12.78
	5	4 – 7	8.61	3.08	23.26	2.17	1.49	3.09
	6	7 – 10	−7.54	2.23	19.44	23.23	5.72	2.21
	7	10 – 13	8.25	−3.62	7.29	−11.48	−11.09	−3.58
	8	13 – 16	−2.27	−4.72	−2.07	−18.66	5.10	−4.77
	9	16 – 19	−0.88	−11.92	−3.69	−15.88	19.35	−12.11
	10	19 – 23	1.85	−9.73	−16.29	−27.01	−33.45	−9.53
	11	23 – 28	−2.20	−12.07	7.06	33.13	122.1	−12.64
	12	28 – 33	0.53	−8.30	−9.53	−11.52	−29.78	−8.11
	13	33 – 39	−2.73	−5.21	−23.68	−48.09	−47.39	−4.36
	14	Over 39	35.56	−19.79	−48.09	−12.80	−15.48	−19.91

3.6 Combined Runs Approach Results

Average road grade and precision, number of runs and precision, effect of road grade magnitude on precision, and benchmark comparisons to LIDAR-based road grade are presented in this section.

3.6.1 Average Road Grade and Precision

The average road grade profile and 95% confidence intervals were estimated for a total of 1116 segments of Δd=0.10 miles (0.16 km) along all routes of the study design. The analysis was repeated for three cases based on the number of GPS runs: 9 GPS runs; 18 GPS runs, and 36 GPS runs. Because three receivers were used simultaneously, three GPS runs are collected based on just one vehicle run along the study routes. Three vehicle runs, or 9 GPS runs, were selected as a baseline. Since the precision of the estimate is inversely proportional to the square root of number of repeated runs, the precision is expected to become smaller (better) by 30% based on doubling the number of runs to 18, and by 50% based on quadrupling the number of runs to 36.

As an example of the results, the average and precision of road grade estimates for Route 3I are shown in Figure 3.8 based on 36 runs. Road grade varies from -8.3 percent at a cumulative distance of 17.3 miles to $+6.9$ percent at a cumulative distance of 16.7 miles. The average road grade precision is 0.18 percent with standard deviation of 0.06 percent. All of the segments have precision of ± 0.4 percent grade or better. Therefore, combining 36 GPS runs from 12 vehicle runs completely satisfies the desired precision of ± 0.5 percent grade.

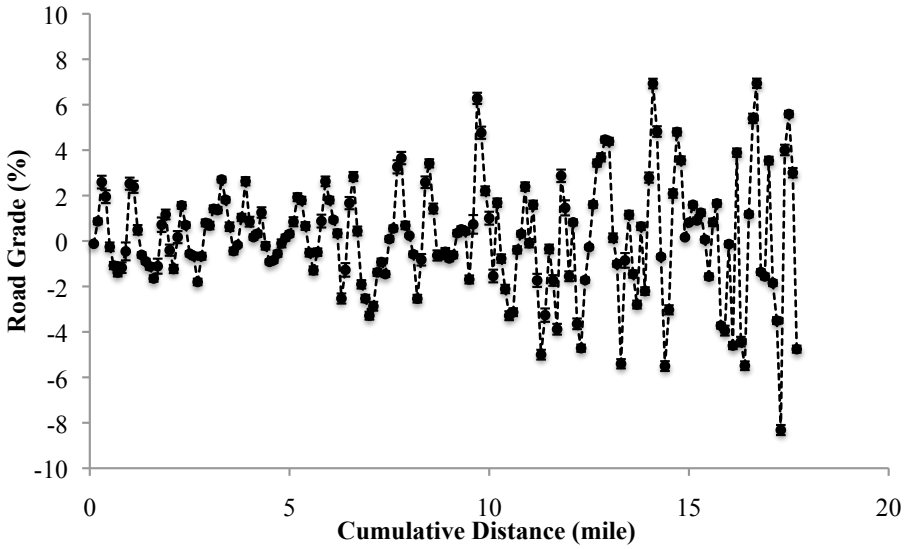


Figure 3.8: Average road grade and 95% confidence interval on the average based on combining 36 Garmin GPS runs for Route 3I, Δd=0.10 miles.

3.6.2 Number of Runs and Precision

As the number of combined GPS runs decreases, precision is worsened. Figure 3.9 illustrates the distribution of observed road grade precisions based on combining 36, 18, and 9 GPS runs for all of 8 routes. The average precision is 0.16, 0.25, and 0.39 percent grade, respectively, with corresponding standard deviations of 0.07, 0.11, and 0.18 percent grade. The proportion of segments that have road grade precision within the target of $\pm$0.5 percent grade or better are 99.8 percent for 36 runs, 98 percent for 18 runs, and 80 percent for 9 runs.

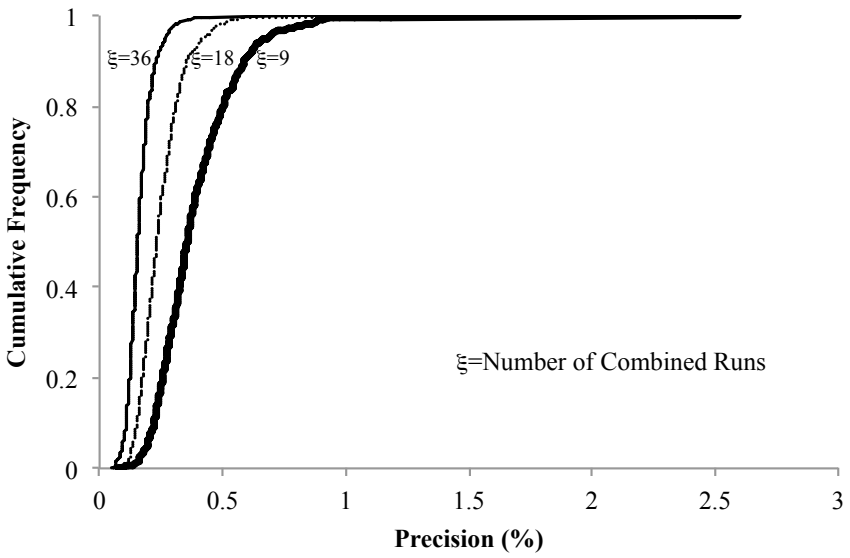


Figure 3.9: Cumulative frequency distribution of road grade precision obtained from combining 9, 18, and 36 Garmin GPS runs based on all of 8 routes, Δd=0.10 miles.

3.6.3 Effect of Road Grade Magnitude on Precision

As the average road grade increases, it is hypothesized that the precision will worsen because deviations from a truly linear slope will lead to more estimation error, and such errors may be more pronounced as the average slope increases. To evaluate this hypothesis, the average precision based on 36 runs is stratified into road grade ranges, as shown in Figure 3.10. The trend in the average precision versus grade is well described by a parabolic trend line. As expected, the average precision worsens as the magnitude of grade increases. There is substantial variability in the precision within a road grade range. The average estimates are typically greater than the median estimates because precision must be nonnegative and, therefore, the statistical distribution of precision is

positively skewed.

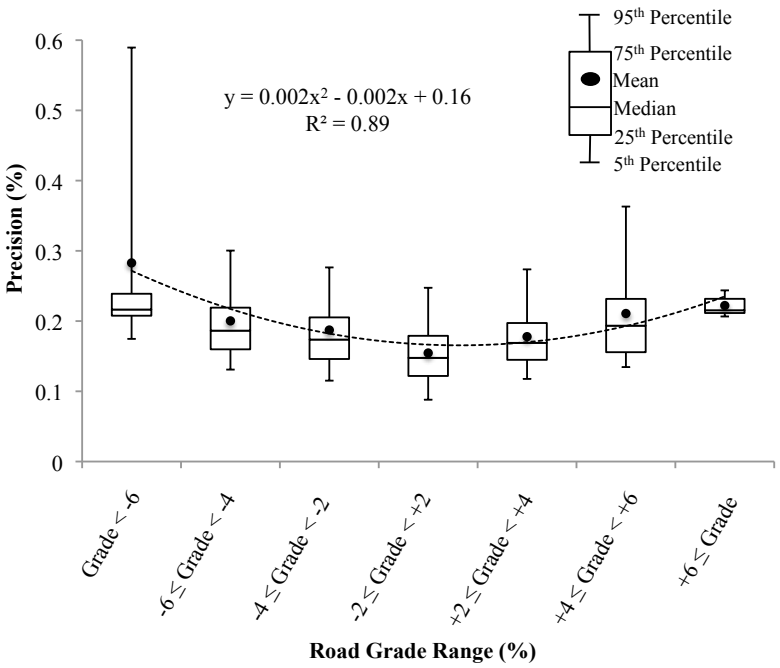


Figure 3.10: Relationship between precision and road grade magnitude obtained from combining 36 GPS runs based on all of 8 routes, Δd=0.10 miles.

3.6.4 Benchmark Comparison of GPS with LIDAR-Based Road Grade

LIDAR-based estimates of road grade were previously developed for the study routes of Figure 2.3 (Zhang and Frey 2006). LIDAR-based grade estimates for portions of I-40 and I-540 were compared to and found to agree with grades estimated from design drawing data. Although there are some limitations of LIDAR data, such as for estimating the slope of road surfaces on or below bridges, this is the best available independent source

of grade data for the study routes.

Figure 3.11 compares road grade obtained from GPS/BA and LIDAR data for Route 3I. There are many similarities in the location and magnitude of positive and negative peaks in grade, such as between 3 and 7 miles cumulative distance. There are also some differences. For example, at approximately 9 miles, the LIDAR-based data imply more variability in grade than the CGPS/BA data. There are a series of overpasses near this location, which confound the LIDAR data. Thus, the CGPS/BA data are likely to be more accurate in this case. At other locations, the magnitude of the grade is similar, but the location differs slightly, such as at approximately 14 miles and 17 miles. This could be in part because the segment lengths used in LIDAR differ from those used in the CGPS/BA analysis. Overall, the comparison is generally consistent. Similar results were obtained for other routes, except for one location (intersection of Hillsborough Street and Pullen Road) where the road was reconstructed and realigned after the LIDAR measurements were made.

3.7 Differential GPS Results

This section is based on results obtained from 4 runs done by Trimble GeoXH 6,000 series differential GPS. It includes average road grade and precision, benchmark comparison with LIDAR-based road grade, and filling out the gaps in places where DGPS data are invalid, such as underneath a bridge, with Garmin GPS data. Here, DGPS results are obtained from combined runs approach.

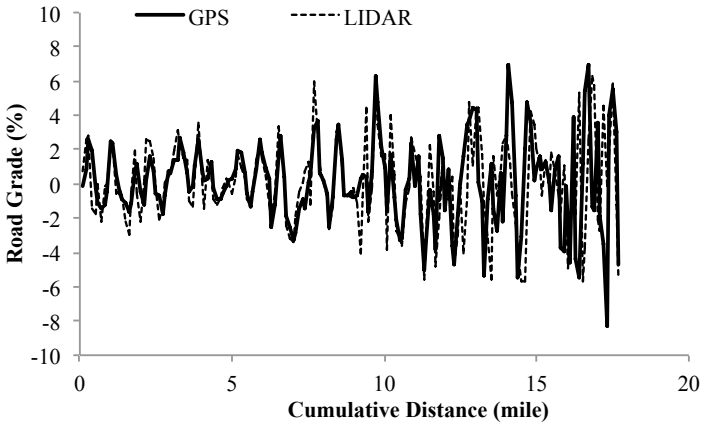


Figure 3.11: Comparison of GPS with LIDAR road grade based on combining 36 GPS runs for Route 3I, Δd=0.10 miles.

3.7.1 Average Road Grade and Precision

Average road grade profile and 95% confidence interval on average for Route 3I are shown in Figure 3.12. Four DGPS runs are combined. Road grade varies from -8.3 at cumulative distance of 17.1 miles to $+8.5$ percent at cumulative distance of 16.5 miles. Average road grade precision is 0.22 percent with standard deviation of 0.18 percent. Approximately 94 percent of segments have precision of within ± 0.5 percent grade. However, DGPS receivers are very sensitive to loss of signal; bridges and trees were observed to obstruct signal reception. For example, at a cumulative distance of 8.8 miles there are several bridges and at 16.6 miles there is high density of trees which affects signal communications between receiver and satellite; results for such locations are assumed to be invalid.

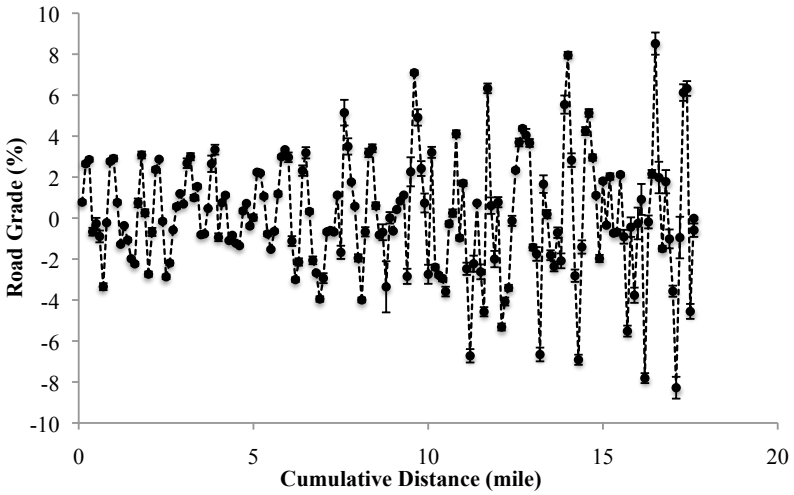


Figure 3.12: Average road grade and 95% confidence interval on the average based on combining 4 DGPS runs for Route 3I, Δd=0.10 miles.

3.7.2 Benchmark Comparison with LIDAR-Based Road Grade

Road grade profiles obtained from DGPS and LIDAR data for Route AO are shown in Figure 3.13. Four DGPS runs are combined. While the two profiles are not exactly the same, peaks and valleys occur at the same location in both data sets. At a given location, road grade values are close to each other in both profiles. For example, at the cumulative distance of 5.9 miles there is a peak in both profiles; road grade obtained from LIDAR is +5.13 percent and the corresponding value obtained from DGPS is +5.08 percent. The apparent disagreement in the first 2 miles of cumulative distance is because of road construction that took place between the time that the LIDAR data were collected and when the DGPS data were collected. Overall, in the entire 8 routes, DGPS results are accurate compared to LIDAR results.

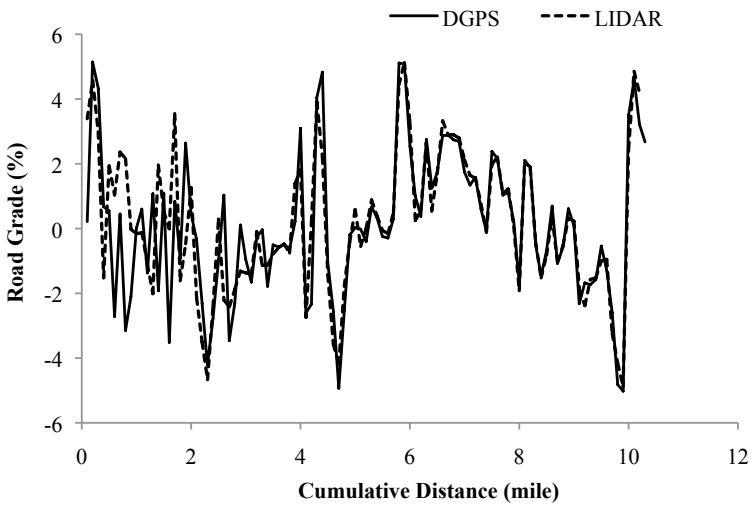


Figure 3.13: Comparison of DGPS with LIDAR road grade for Route AO, Δd=0.10 miles.

3.7.3 Filling DGPS Gaps with Low Cost Receiver Road Grade

The DGPS data logger is very sensitive to objects such as bridges, trees, or buildings that block the satellite signal. When a vehicle is driven underneath a bridge, DGPS communication with satellite is disturbed. The quality of DGPS data can be inferred by looking at second-by-second accuracy, such as for Trimble GeoXH 6,000 series receiver. The typical accuracy of this kind of receiver when it is differentially corrected is about 10 cm both horizontally and vertically. Once there is an overpath such as a bridge, the accuracy can deteriorate to tens of meters. On average, it takes about ten seconds for the DGPS to become stable again at an accurate reading after clearing an overpath; if a vehicle is driven at 65 (mph), it takes about 0.20 miles for the data to return to stable condition. Thus, there is a need to replace the invalid road grade data within the 0.20 miles with a locally more accurate database such as consumer grade GPS with barometric altimeter. Figure 3.14 shows an example where DGPS data is replaced by consumer grade

GPS data; consumer grade GPS road grade shown here is obtained from averaging of 100 runs. This example is on Route 3O, the intersection of Glenwood Avenue with I-540. Four DGPS runs are shown. They agree very well between cumulative distances of 8.4 to 8.8 and 9.2 to 9.5 miles. However, there is an obvious disagreement among the four DGPS runs from cumulative distance of 8.8 to 9.2 miles where the bridge is located and affecting the data; this portion can be replaced by a consumer grade GPS data. From cumulative distance of 8.8 to 9.1 miles, the consumer grade GPS road grade is almost zero percent and the DGPS road grade is 3.5 percent in the worst case; if a vehicle is driven at a constant speed of 55 (mph) under the bridge, VSP is 7.8 (kW/ton) if one uses the consumer GPS road grade (VSP mode 6) and VSP is 16.2 (kW/ton) if one uses the DGPS road grade (VSP mode 9). Thus, using the DGPS road grade at the location of a bridge leads to misestimation of VSP by 3 modes.

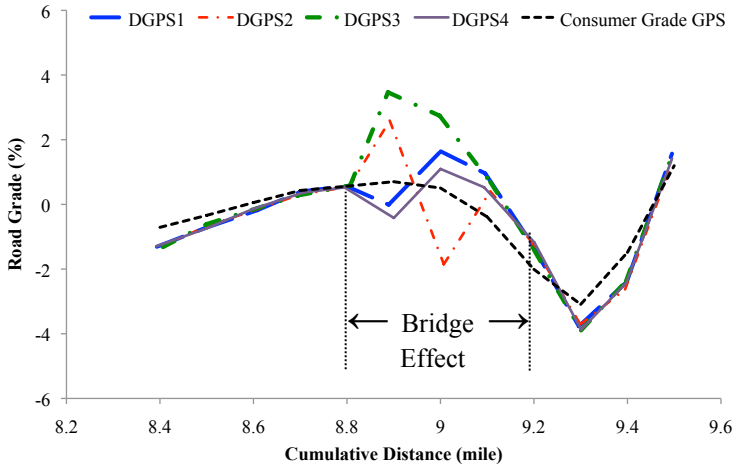


Figure 3.14: Replacing DGPS road grade with average of 100 runs road grade obtained from a low-cost consumer grade GPS underneath a bridge on Route 3O, Δd=0.10 miles.

Chapter 4

Conclusions

Vehicle fuel use and emissions are sensitive to road grade. Road grade is needed to accurately quantify engine load and to calibrate models of vehicle fuel use and emissions; if a proper model that correlates vehicle emissions with road grade is available, the results of such model can even be used in policy making, e.g. how to grade new roads or where to build a school in the road network. If road grade is not estimated accurately, there can be substantial misestimation of localized emissions that affect near-roadway air quality and human exposure to pollutants, and of area-wide estimates that affect urban and regional scale air quality and exposure. As an example, it was shown that for a 2011 Chevrolet HHR, emissions will be overestimated up to 26% if negative road grade is ignored and will be underestimated up to 46% if positive road grade is ignored. Also, if one wants to go from point "A" to point "B" and there are a couple of alternative routes between these two points, road grade can affect the route selection as the smoother the route, the less fuel is consumed. Average estimates of road grade based on a consumer grade standalone GPS receiver with barometric altimeter are shown to be accurate in comparison to LIDAR data, but to be imprecise unless the sample size is sufficiently large. The needed

sample size depends on the desired precision of the average road grade and to a lesser extent on the magnitude of road grade. As shown in sensitivity analysis, VSP is sensitive to changes in road grade but small changes in road grade of only 0.5 percent would not typically lead to large differences in classification in terms of VSP-based operating modes. Thus, such a level of precision is likely to be more than adequate for practical purposes. In Individual Runs approach, average sample size of approximately n = 22 was found to be large enough to obtain confidence intervals on the mean that were typically less than ±0.5 percent grade.

Synchronizing the cumulative distance and elevation data of multiple GPS data, combining them into one dataset and applying the linear regression model to the desired averaging distance could significantly increase the precision. Combining multiple runs into one data set would lead to a larger effective sample size per road segment, and thus a narrower confidence interval on the grade. A narrower confidence interval implies that fewer vehicle runs are needed to achieve a target precision. Precision is inversely proportional to square root of number of combined runs. It was shown that combining 18 consumer grade stand-alone GPS runs will result in road grade estimates that are 98 percent within the target precision of ±0.5 percent grade. Doubling the number of combined runs to 36 will improve the precision; however, if one is looking for a precision of ±0.5 percent grade, 18 runs will suffice. Road grade estimates for segments with higher road grade magnitudes are observed to be less precise compared to flat segments. In general, benchmark comparisions between GPS and LIDAR-based road grade showed concordance in trend of road grade profile and locations where peaks and valleys occur; however, corresponding road grade magnitudes are not the same.

As a result of this research, road grade profile, i.e. road grade values at each cumulative distance, is available for the routes explored here (**A**, **1**, **C**, **3**). So, calculated road grades based on multiple runs can be used in VSP equation for each test instead of road grades that are solely based on one GPS run. However, one GPS receiver should be used in each test to record position so that it can be synchronized based on cumulative distance traveled with the road grade profiles obtained from multiple runs.

Although consumer grade stand-alone GPS receivers with barometric altimeters are not the only available choice for quantifying road grade, they are a useful choice if equipment costs must be low and if there is the opportunity for repeated measurements of the same routes. However, for routes that will be measured only once, other alternatives should be explored, such as the use of DGPS or LIDAR data.

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APPENDICES

Appendix A

Individual Runs Approach Results

Average road grade profiles and 95% confidence interval on mean road grade for all 8 routes are shown. Also, benchmark comparisions with LIDAR-based road grade for each route is illustrated here. The results are based on Individual Runs approach with approximately 100 runs with CGPS/BA. Below is the table that summarizes the average precision and standard deviation of precisions for each one-way route.

Table A.1: Average and Standard Deviation of Precisions for Each Route Based on 0.10 mile Segments

Route	**Average Precision** (%)	**Precision Standard Deviation** (%)
AO	0.19	0.06
1O	0.16	0.06
1I	0.15	0.06
AI	0.18	0.07
CO	0.22	0.09
3O	0.31	0.12
3I	0.31	0.11
CI	0.26	0.08

A.1 Average Road Grade with 95% Confidence Interval on Mean Based on 0.10 mile Segments

Route A

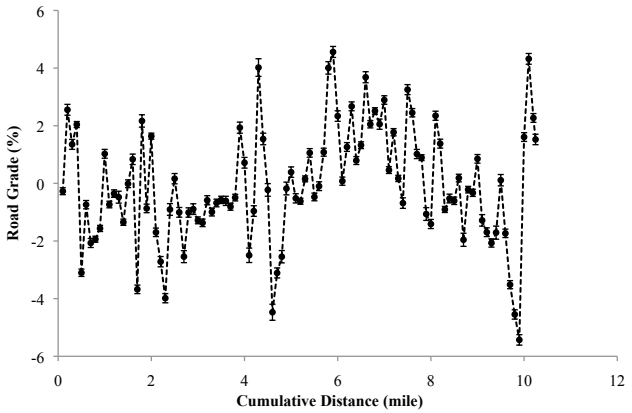

Figure A.1: **A Outbound**

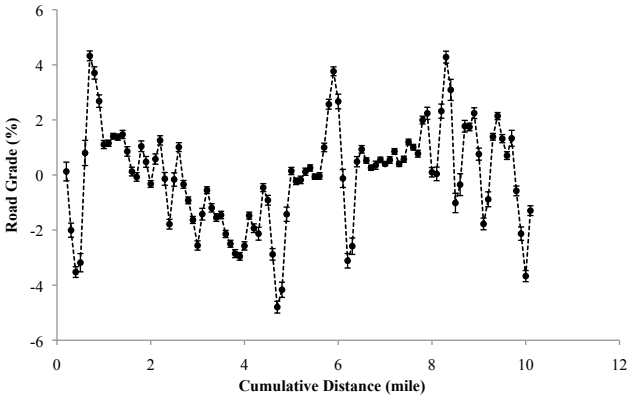

Figure A.2: **A Inbound**

Route 1

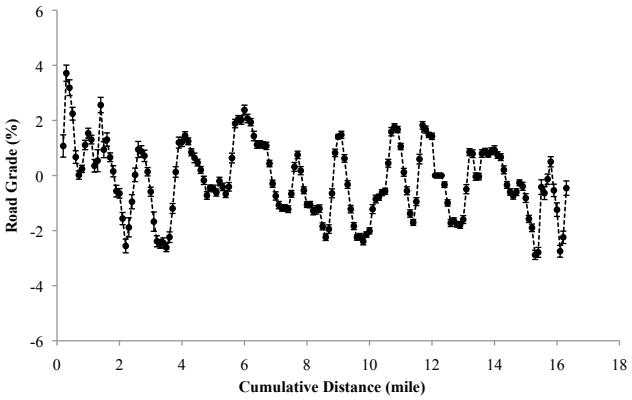

Figure A.3: **1 Outbound**

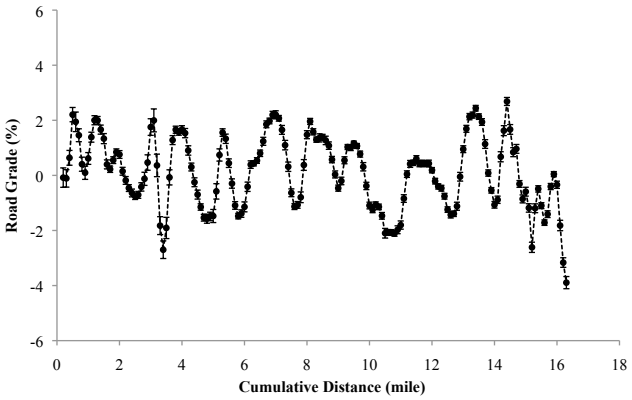

Figure A.4: **1 Inbound**

Route C

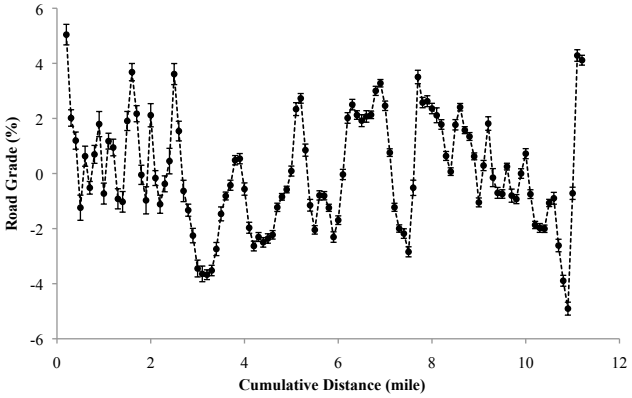

Figure A.5: **C Outbound**

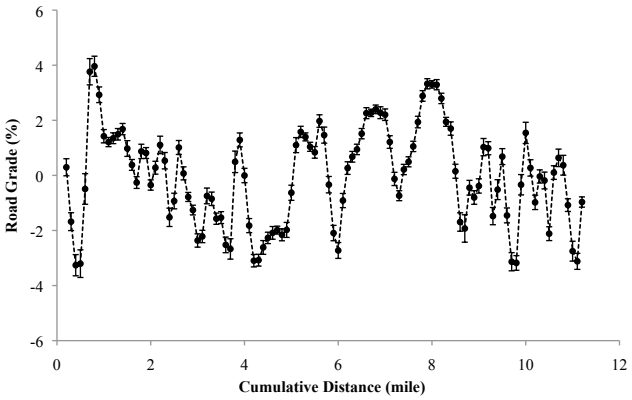

Figure A.6: **C Inbound**

Route 3

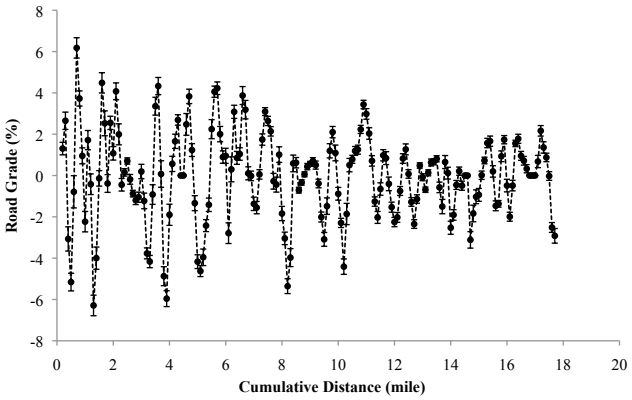

Figure A.7: **3 Outbound**

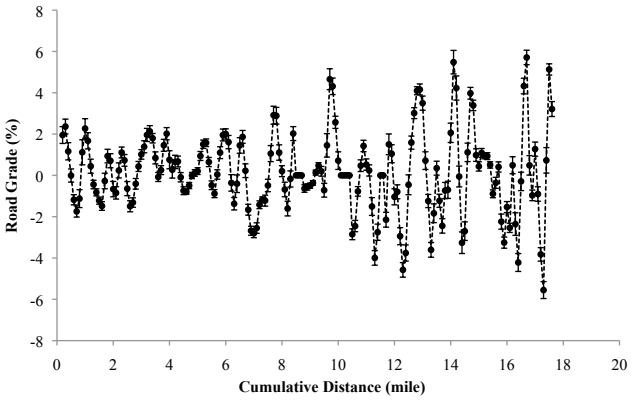

Figure A.8: **3 Inbound**

A.2 Benchmark Comparison of GPS with LIDAR-Based Road Grade

Route A

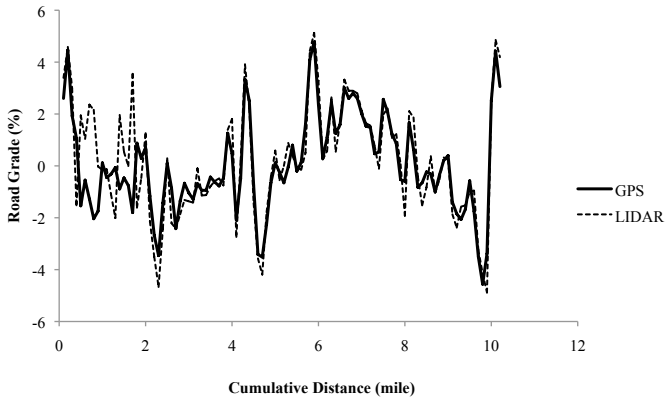

Figure A.9: **A Outbound**

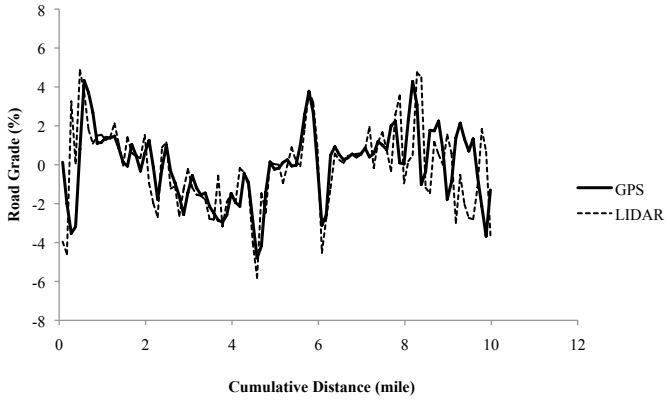

Figure A.10: **A Inbound**

Route 1

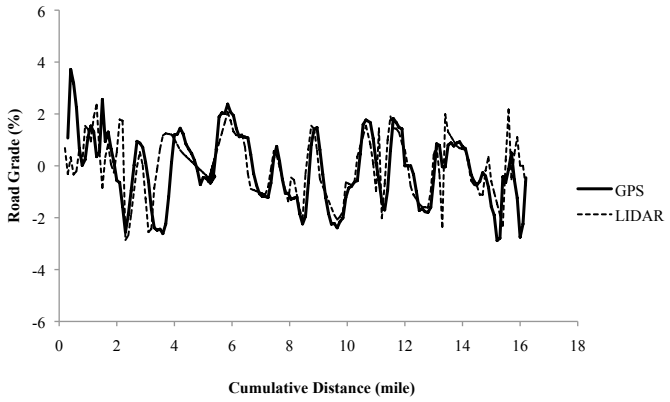

Figure A.11: **1 Outbound**

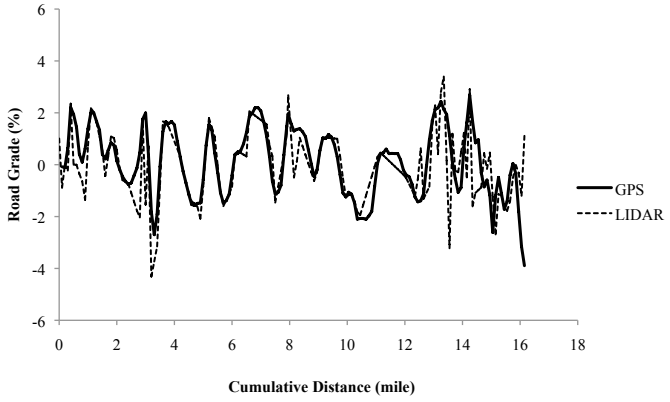

Figure A.12: **1 Inbound**

Route C

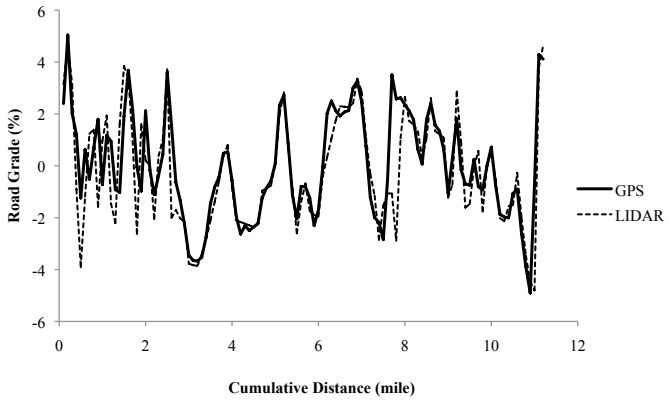

Figure A.13: **C Outbound**

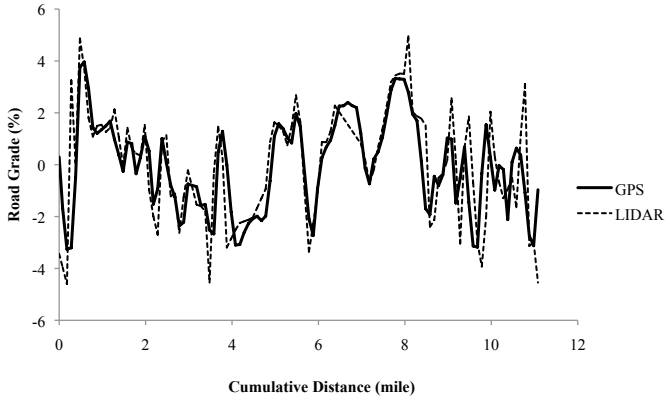

Figure A.14: **C Inbound**

Route 3

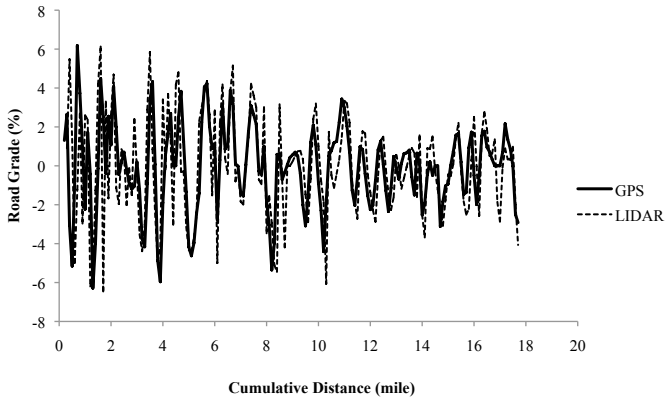

Figure A.15: **3 Outbound**

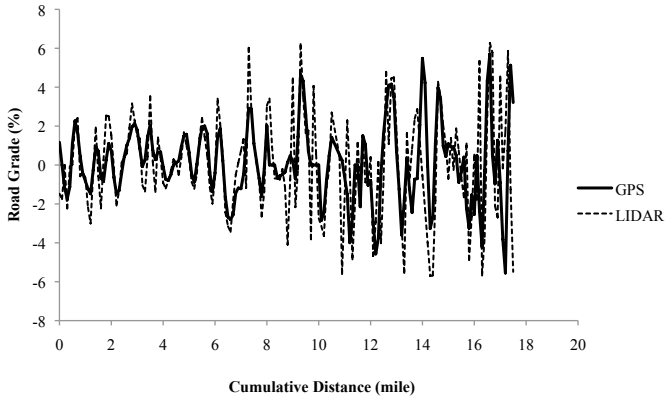

Figure A.16: **3 Inbound**

Appendix B

Combined Runs Approach Results

Average road grade profiles and 95% confidence interval on mean road grade for all 8 routes are shown. Also, benchmark comparisions with LIDAR-based road grade for each route is illustrated here. The results are based on Combined Runs approach with 36 runs with CGPS/BA. Below is the table that summarizes the average precision and standard deviation of precisions for each one-way route.

Table B.1: Average and Standard Deviation of Precisions for Each Route Based on 0.10 mile Segments

Route	**Average Precision** (%)	**Precision Standard Deviation** (%)
AO	0.16	0.04
1O	0.17	0.04
1I	0.15	0.04
AI	0.13	0.04
CO	0.15	0.04
3O	0.19	0.06
3I	0.18	0.06
CI	0.15	0.06

B.1 Average Road Grade with 95% Confidence Interval on Mean Based on 0.10 mile Segments

Route A

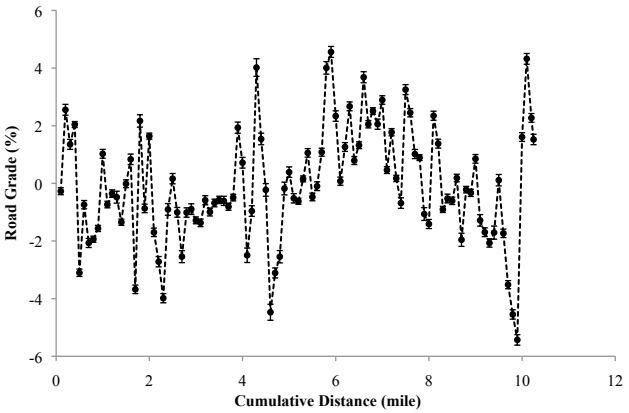

Figure B.1: **A Outbound**

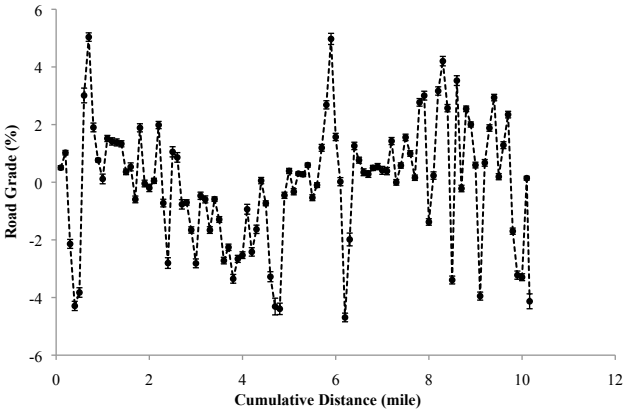

Figure B.2: **A Inbound**

Route 1

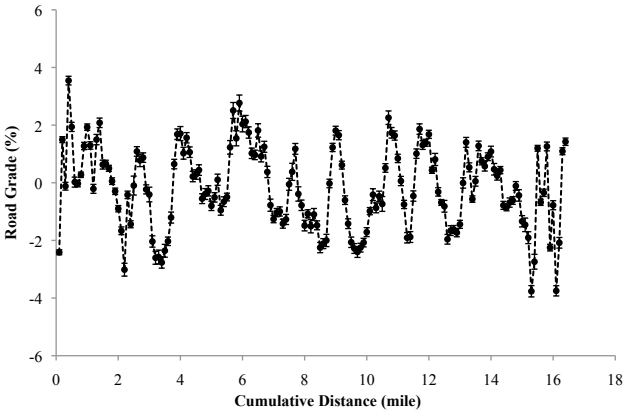

Figure B.3: **1 Outbound**

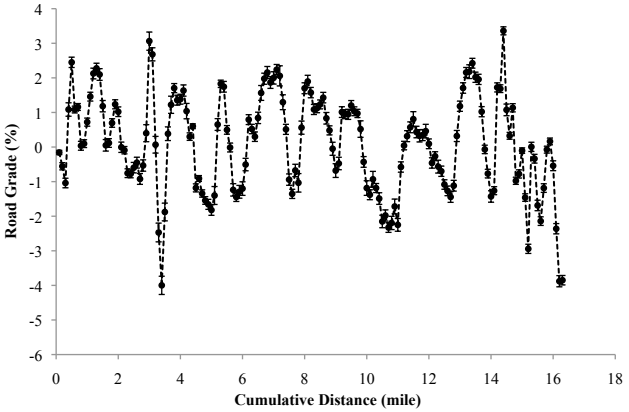

Figure B.4: **1 Inbound**

Route C

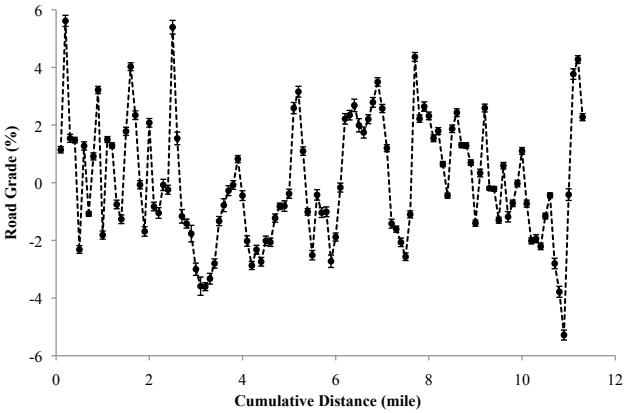

Figure B.5: **C Outbound**

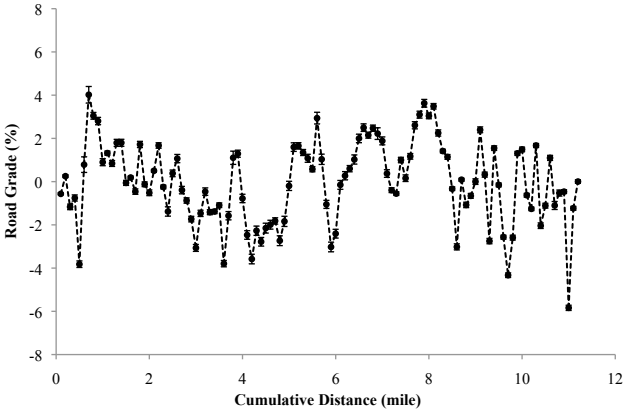

Figure B.6: **C Inbound**

Route 3

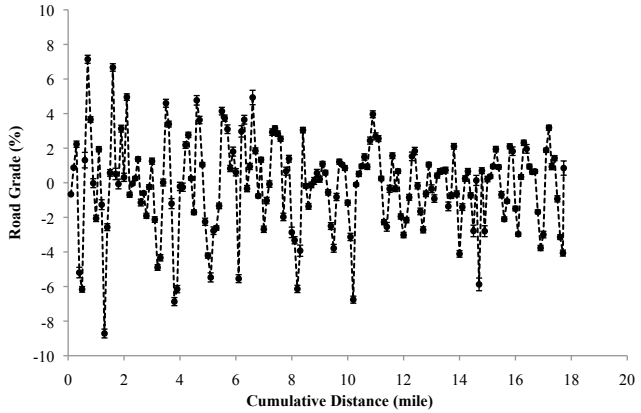

Figure B.7: **3 Outbound**

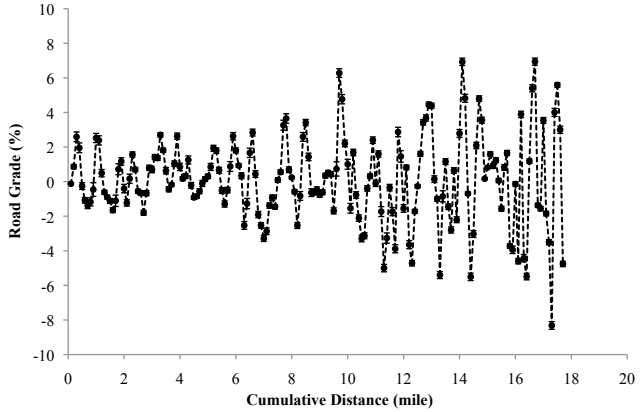

Figure B.8: **3 Inbound**

B.2 Benchmark Comparison of GPS with LIDAR-Based Road Grade

Route A

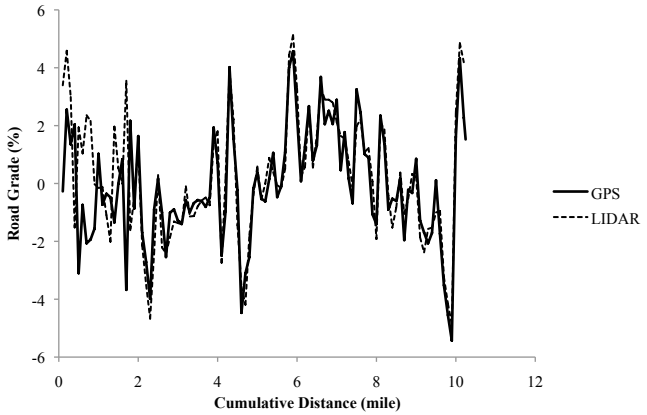

Figure B.9: **A Outbound**

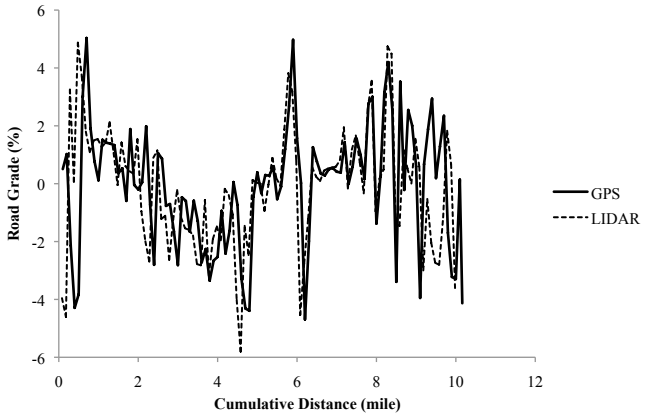

Figure B.10: **A Inbound**

Route 1

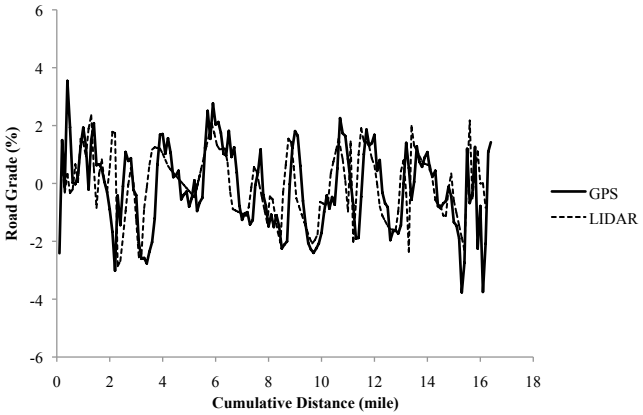

Figure B.11: **1 Outbound**

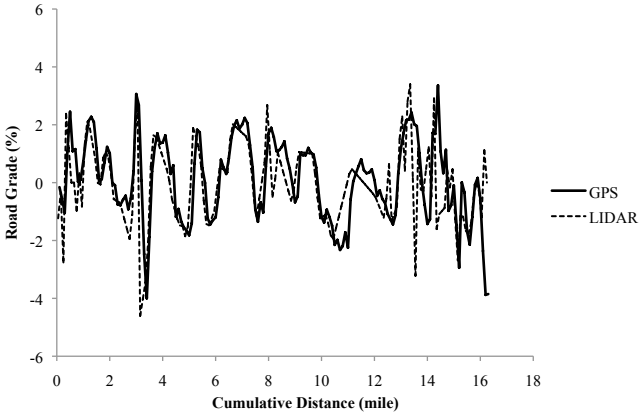

Figure B.12: **1 Inbound**

Route C

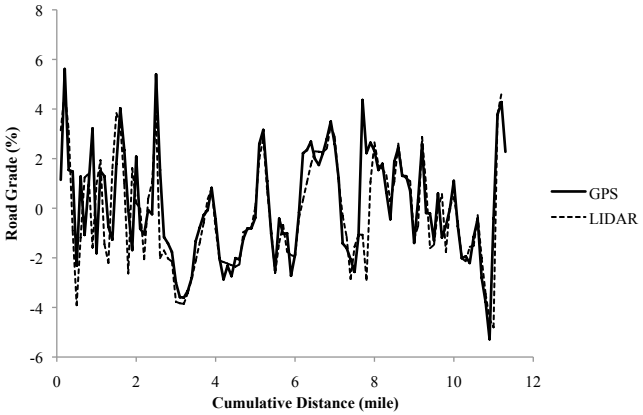

Figure B.13: **C Outbound**

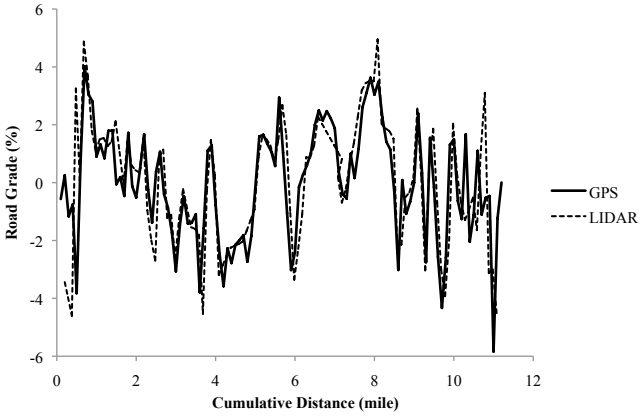

Figure B.14: **C Inbound**

Route 3

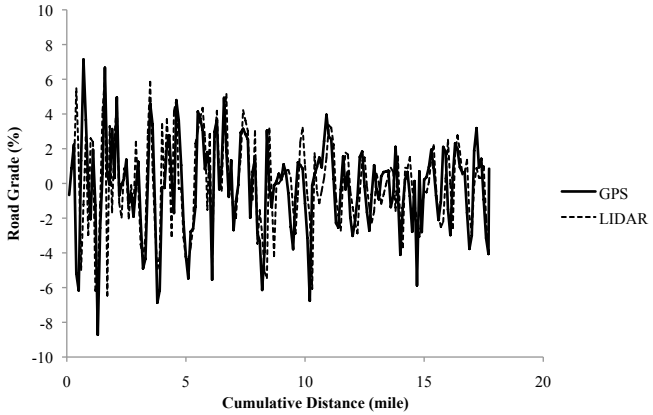

Figure B.15: **3 Outbound**

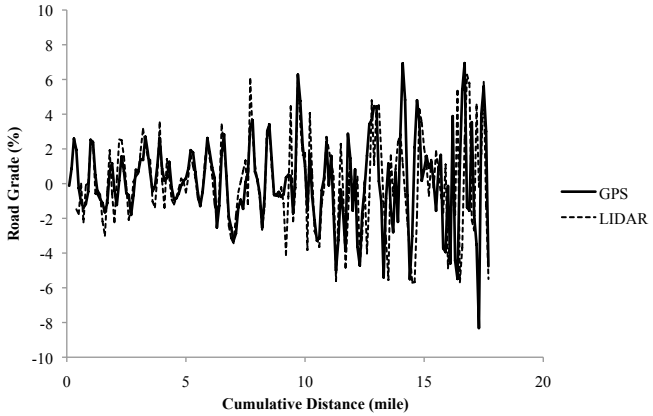

Figure B.16: **3 Inbound**

Appendix C

Differential GPS Results Based on Combined Runs Approach

Average road grade profiles and 95% confidence interval on mean road grade for all 8 routes are shown. Also, benchmark comparisions with LIDAR-based road grade for each route is illustrated here. The results are based on Combined Runs approach with 4 runs with DGPS. Below is the table that summarizes the average precision and standard deviation of precisions for each one-way route.

Table C.1: Average and Standard Deviation of Precisions for Each Route Based on 0.10 mile Segments

Route	**Average Precision (%)**	**Precision Standard Deviation (%)**
AO	0.21	0.19
1O	0.15	0.16
1I	0.17	0.18
AI	0.17	0.12
CO	0.17	0.14
3O	0.23	0.18
3I	0.22	0.18
CI	0.19	0.16

C.1 Average Road Grade with 95% Confidence Interval on Mean Based on 0.10 mile Segments

Route A

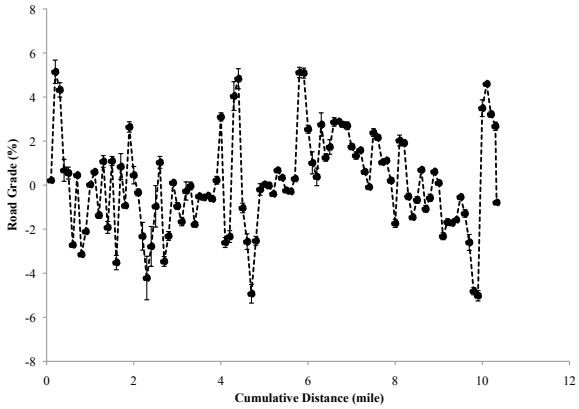

Figure C.1: **A Outbound**

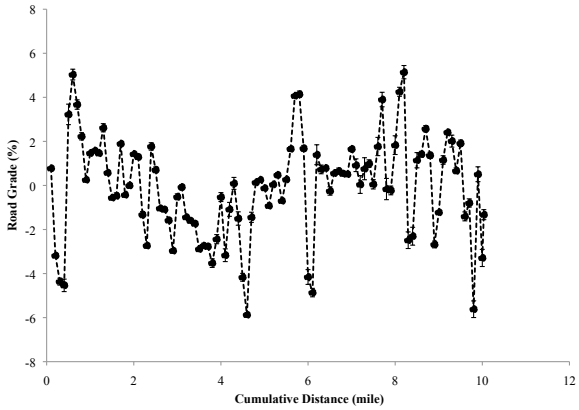

Figure C.2: **A Inbound**

Route 1

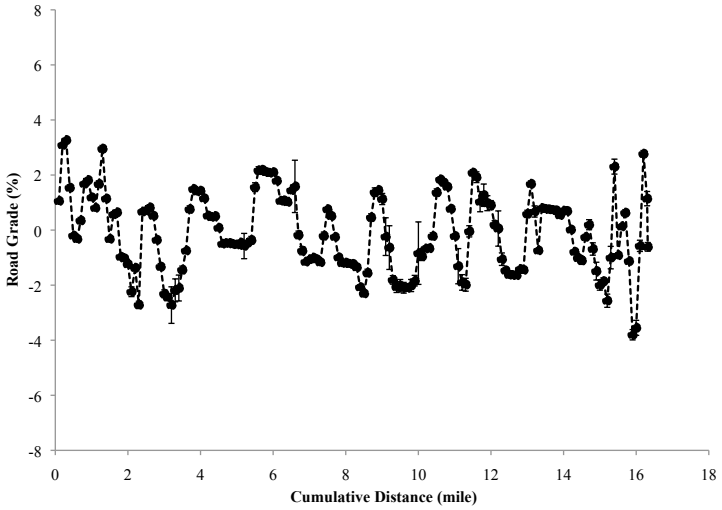

Figure C.3: **1 Outbound**

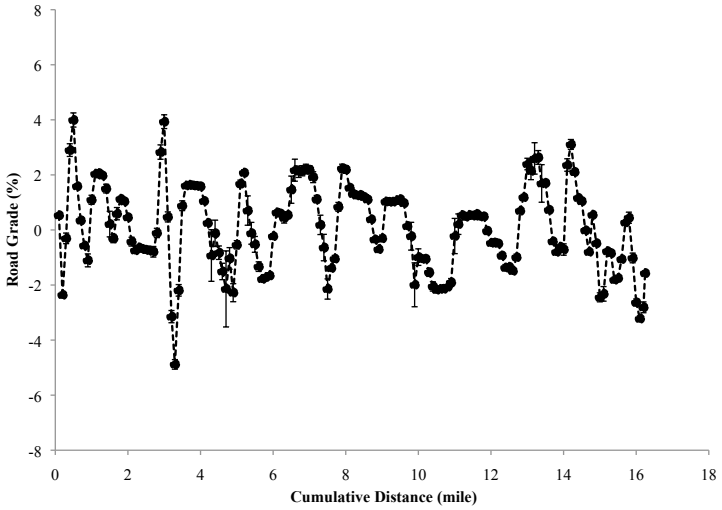

Figure C.4: **1 Inbound**

Route C

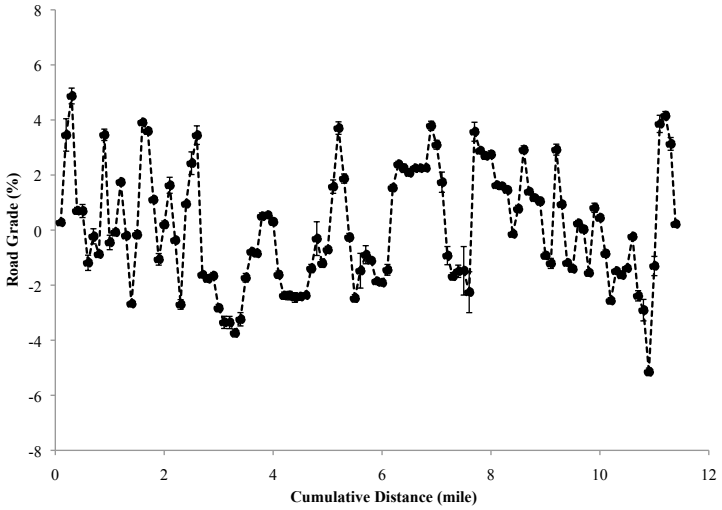

Figure C.5: **C Outbound**

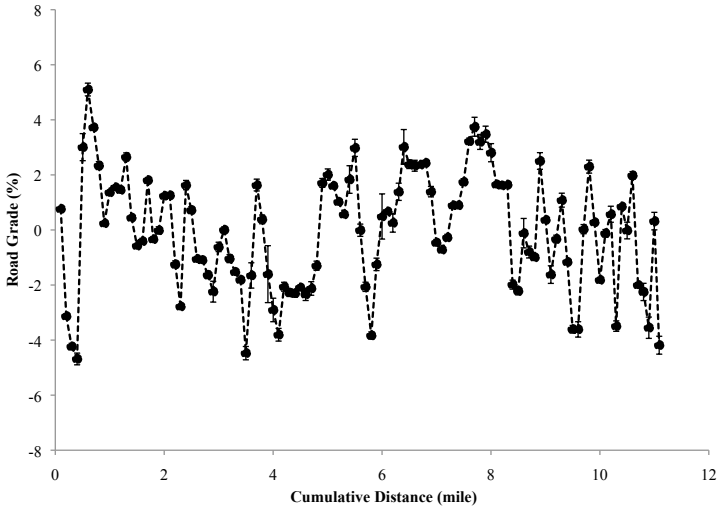

Figure C.6: **C Inbound**

Route 3

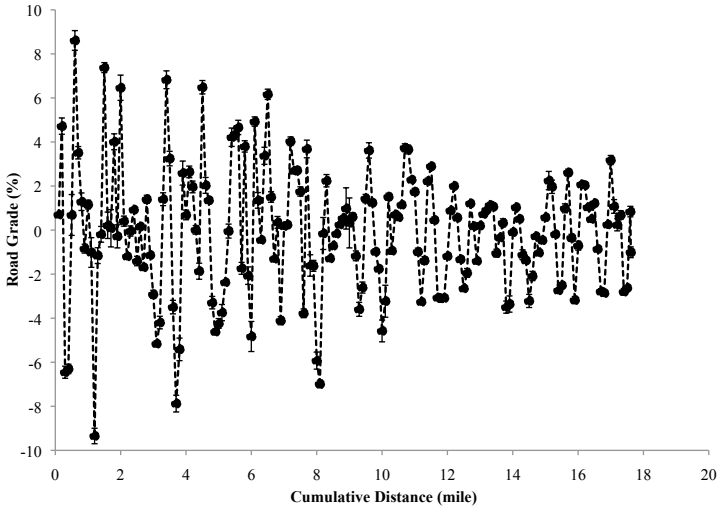

Figure C.7: **3 Outbound**

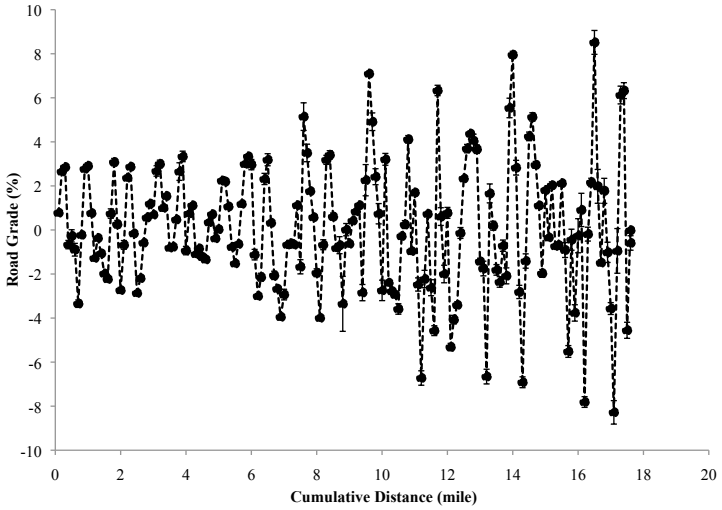

Figure C.8: **3 Inbound**

C.2 Benchmark Comparison of GPS with LIDAR-Based Road Grade

Route A

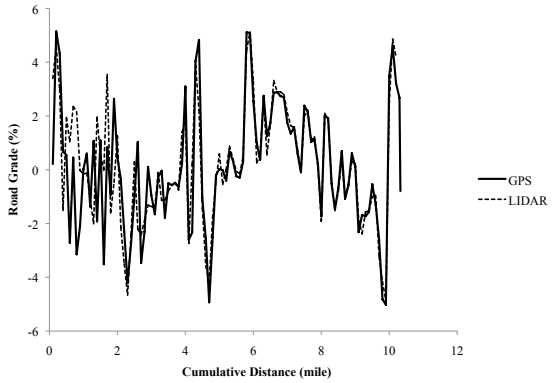

Figure C.9: **A Outbound**

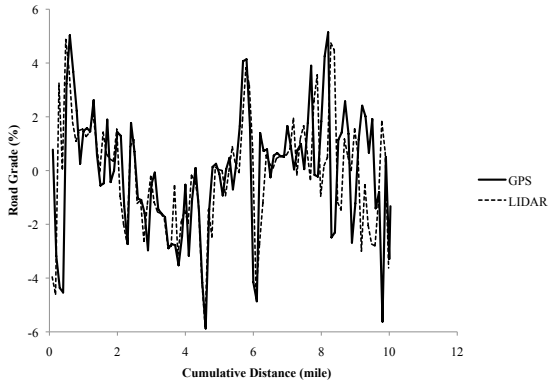

Figure C.10: **A Inbound**

Route 1

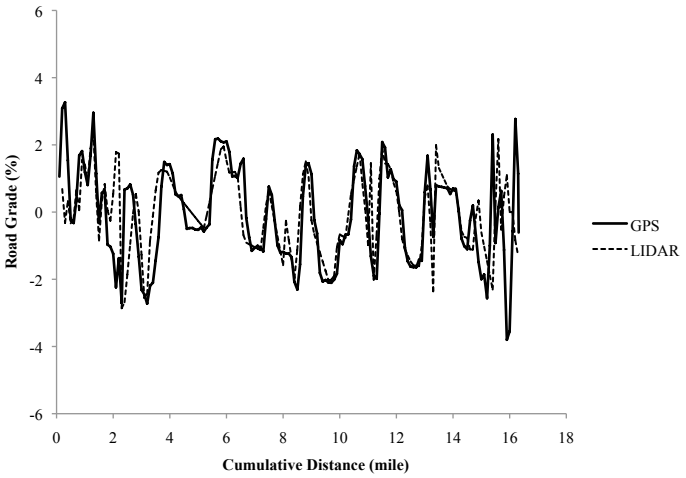

Figure C.11: **1 Outbound**

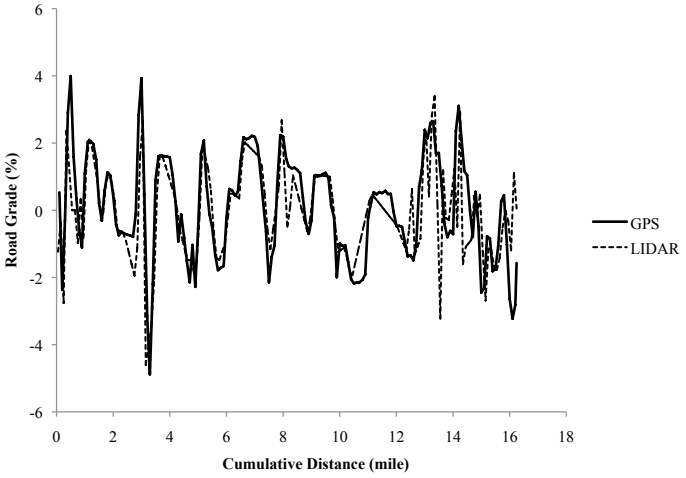

Figure C.12: **1 Inbound**

Route C

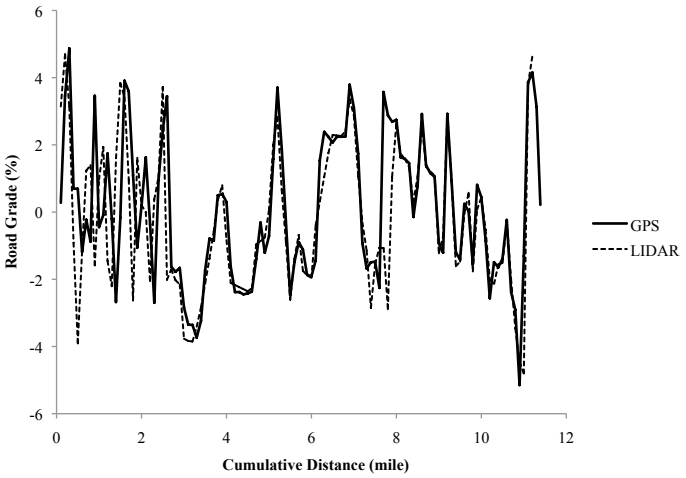

Figure C.13: **C Outbound**

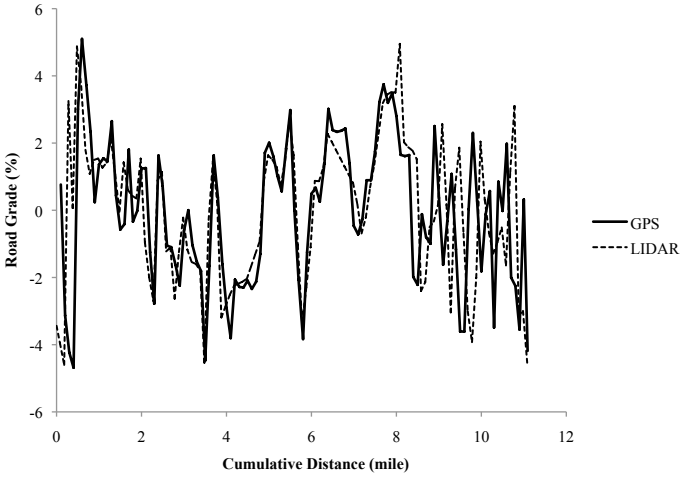

Figure C.14: **C Inbound**

Route 3

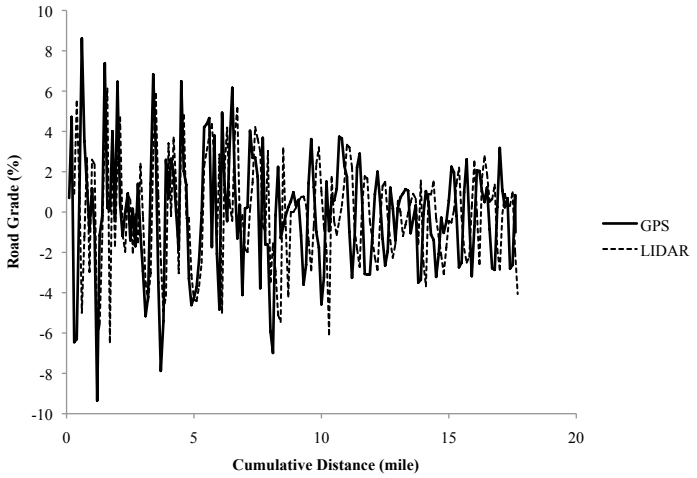

Figure C.15: **3 Outbound**

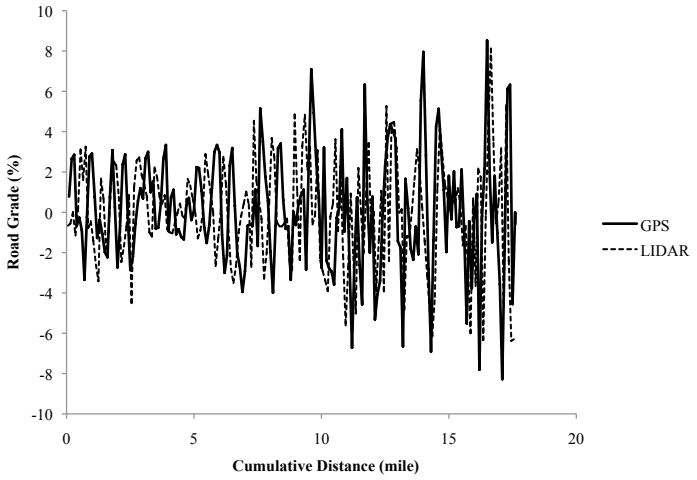

Figure C.16: **3 Inbound**

Appendix D

MATLAB Code Used to Implement Vertical Alignment and Calculate Road Grade Precision in the Combined Runs Approach

The following code is used for vertical alignment of multiple GPS runs in the Combined Runs approach. As explained in section 2.6.3, vertical alignment among multiple runs is needed before combining them into one data set. The following code has three inputs: 1) desired run (Latitude, Longitude, Elevation), 2) reference average elevation for every 0.10 mile segment, and 3) true cumulative distance of the route. The code calculates the cumulative distance for the desired run and applies the distance correction factor on each second of data and does the vertical alignment as explained in Figure 2.4. The output is the second-by-second corrected cumulative distance and corrected elevation for the desired run.

```
The inputs for this code are: 1) second-by-second of raw GPS data
(Latitude, Longitude, Elevation), 2) average reference elevation for
every 0.10 mile, 3) true cumulative distance.
This code calculates the observed second-by-second distance, applies
distance correction factor to it and does the elevation alignment
(correction) for every 0.10 mile.
The output is corrected cumulative distance and corrected elevation
(second-by-second).


function [All_Results Cor_Cum_Dist_SI Cor_Cum_Dist Cor_Elevation
Label_Cum_Dist Number_Labels] = software(Matrix1,Matrix2,true_dist)
%%Insert the input raw latitude, longitude, and elevation data
[n_row1 n_col1]=size(Matrix1);
Latitude=Matrix1(:,1);
Longitude=Matrix1(:,2);
Elevation=Matrix1(:,3);
%%Calculate the distance traveled from each second to the next and also
%%cumulative distance
Dist=zeros(n_row1,1);
Cum_Dist=zeros(n_row1,1);
for i=2:n_row1
Dist(i)=(((Latitude(i)-Latitude(i-1))*110955)^2+...
((Longitude(i)-Longitude(i-1))*111319*cos(Latitude(i-
1)*pi/180))^2)^0.5*0.000621371192;
Cum_Dist(i)=Dist(i)+Cum_Dist(i-1);
end
%%Applying distance correction factor to each second of data
Dist_SI=Dist*1609.344;
Cum_Dist_SI=Cum_Dist*1609.344;
Cor_Cum_Dist=Cum_Dist*true_dist/Cum_Dist(end);
Cor_Cum_Dist_SI=Cum_Dist_SI*true_dist/Cum_Dist(end);
%%Labeling every 0.10 mile of data and correcting the average elevation
%%of each segment to the reference average elevation
Label_Cum_Dist=floor(Cor_Cum_Dist*10)+1;
n_label=max(Label_Cum_Dist);
Av_Elevation=zeros(n_label,1);
Cor_Elevation=zeros(n_row1,1);
Number_Labels=zeros(n_label,1);
for i=1:n_label
Ind=find(Label_Cum_Dist==i);
Av_Elevation(i)=mean(Elevation(Ind));
Cor_Elevation(Ind)=Matrix2(i)-Av_Elevation(i)+Elevation(Ind);
Number_Labels(i)=numel(Ind);
end
All_Results=[Cor_Cum_Dist_SI';Cor_Cum_Dist';Cor_Elevation';Label_Cum_Di
st']';
end
```

The following code is used to calculate road grade for every 0.10 mile of the combined data set using linear regression and also 95 percent confidence interval on the average road grade. The inputs are: 1) cumulative distance, and 2) elevation. The outputs are cumulative distance, road grade, and standard error of the average road grade. Standard error multiplied by coverage gives the road grade precision.

The inputs for this code are corrected cumulative distance and corrected elevation for every second of data or for the combined run.
This code calculates the average road grade for every 0.10 mile and standard error on the average road grade.
The main outputs are average road grade and standard error on average road grade.

```
function [avg_x avg_y sxx sxy mse Beta1 Beta0
se]=analyse_data(mydata,num_label)
%%Labeling every 0.10 mile of data
n=size(mydata,1);
k=ones(1,num_label);
for data_iter=1:n
for label_iter=1:num_label
if mydata(data_iter,3)==label_iter
M(k(label_iter),1,label_iter)=mydata(data_iter,1);
M(k(label_iter),2,label_iter)=mydata(data_iter,2);
k(label_iter)=k(label_iter)+1;
end
end
end
%%Averaging cumulative distance and elevation for every 0.10 mile and
%%calculating sxx, sxy, and average road grade based on linear
%%regression on every 0.10 mile
avg_x=zeros(num_label,1);
avg_y=zeros(num_label,1);
sxx=zeros(num_label,1);
sxy=zeros(num_label,1);
size_label=zeros(num_label,1);
mse=zeros(num_label,1);
Beta1=zeros(num_label,1);
Beta0=zeros(num_label,1);
se=zeros(num_label,1);
%%Calculating standard error on average road grade (Beta1); standard
%%error multiplied by coverge give the precision of road grade. For
%%large effective sample sizes (n>30), coverage is 1.96.
for label=1:num_label
data=data_give_label (M,label);
x=data(:,1);
y=data(:,2);
avg_x(label)=mean(x);
avg_y(label)=mean(y);
sxx(label)=(x-mean(x))'*(x-mean(x))+1e-20;
sxy(label)=(x-mean(x))'*(y-mean(y));
size_label(label)=numel(x);
Beta1(label)=sxy(label)/(sxx(label));
Beta0(label)=avg_y(label)-Beta1(label)*avg_x(label);
yhat=Beta1(label)*x+Beta0(label);
mse(label)=(y-yhat)'*(y-yhat)/(size_label(label)-2);
se(label)=sqrt(mse(label)/sxx(label));
end
```