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Alexander Y. Bigazzi

Portland State University, abigazzi@gmail.com

Miguel A. Figliozi

Portland State University, figliozi@pdx.edu

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Citation Details

Bigazzi, Alexander Y. and Figliozi, Miguel A., "Dynamic Ventilation and Power Output of Urban Bicyclists" (2015). *Civil and Environmental Engineering Faculty Publications and Presentations*. 314.

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Dynamic Ventilation and Power Output of Urban Bicyclists

Alexander Y. Bigazzi

Department of Civil and Environmental Engineering, Portland State University

P.O. Box 751, Portland, Oregon 97207-0751, USA

Phone: 503-725-4282, Fax: 503-725-5950

Email: abigazzi@pdx.edu

Miguel A. Figliozzi

Department of Civil and Environmental Engineering, Portland State University

P.O. Box 751, Portland, Oregon 97207-0751, USA

Phone: 503-725-4282, Fax: 503-725-5950

Email: figliozzi@pdx.edu

Forthcoming 2015 Transportation Research Record

ABSTRACT

Bicyclist intake of air pollutants is linked to physical exertion levels, ventilation rates, and exposure concentrations. Whereas exposure concentrations have been widely studied in transportation environments, there is relatively scant research linking on-road ventilation with travel conditions and exertion levels. This paper investigates relationships among power output, heart rate, and ventilation rate for urban bicyclists. Heart rate and ventilation rate were measured on-road and combined with power output estimates from a bicycle power model. Dynamic ventilation rates increased by 0.4-0.8% per watt of power output, with a mean lag of 0.8 minutes. The use of physiology (ventilation) monitoring straps and heart rate proxies for dynamic on-road ventilation measurements are discussed. This paper provides for a clearer and more quantitative understanding of bicyclists' ventilation and power output, which is useful for studies of pollutant inhalation risks, energy expenditure, and physical activity.

INTRODUCTION

Active travelers experience conflicting health effects from physical activity on urban streets. Increased regular physical activity leads to well-established health benefits. At the same time, greater physical exertion leads to increased ventilation¹ and in turn greater inhalation of traffic-related air pollution (I). Although high ventilation rates for bicyclists are documented in the literature, existing studies of pollutant inhalation analyzed and reported ventilation rates by mode or trip (2). Little is known about how bicyclists' ventilation varies with travel conditions and over the course of a trip.

The pollutant inhalation rate I is the product of the exposure concentration (C) and ventilation rate (\dot{V}_E). Ventilation rate \dot{V}_E (also called “minute ventilation”) is the product of the breathing frequency f_b and tidal volume V_T . Hence, inhalation rate (in mass per unit time) is calculated

$$I = C \cdot \dot{V}_E = C \cdot f_b \cdot V_T$$

where C is in mass per volume of air, V_E is in volume of air per unit time, f_b is in breaths per unit time, and V_T is in volume of air per breath. Beyond inhalation rate, particle deposition and location of gas absorption in the respiratory tract are affected by the relative values of f_b and V_T , in addition to other factors such as fraction oral breathing (2).

Energy expenditure or power output is a key factor determining respiration and ventilation. Low to moderate levels of energy expenditure utilize aerobic respiration which requires inhalation of oxygen. Up to the anaerobic threshold, ventilation rate \dot{V}_E is closely related to the volume rate of oxygen inhalation (\dot{V}_{O_2}). \dot{V}_E increases primarily by an increase in V_T at lower levels of exertion, then increasingly by f_b . At 70-80% of peak exercise level f_b becomes the dominant factor, although professional bicyclists can achieve a greater effect through V_T (3, 4).

One previous study directly measured dynamic on-road ventilation rates while bicycling for the purpose of pollutant dose estimation, although analysis of ventilation was not provided (5). That study used a facemask system to measure ventilation – a method also used in other on-road (6) and laboratory (1) study settings. Another approach has been to estimate dynamic on-road ventilation rate (\dot{V}_E) from measured heart rate (HR), based on laboratory-derived $\dot{V}_E \sim HR$ relationships for individual subjects (7, 8). Laboratory \dot{V}_E measurements typically use a bicycle ergometer (stationary bicycle) and a facemask.

Figure 1 illustrates the connection between bicyclist ventilation and travel conditions. A rider's energy expenditure affects heart and ventilation rates, mediated by individual subject physiology (and to a lesser degree other variables such as air density). At the same time, the energy expenditure above baseline or resting metabolic rate leads to a commensurate energy transfer to the bicycle, mediated by bicycle attributes and the style of riding (pedaling cadence, upper body control, etc.). The energy transferred to the bicycle produces a certain travel speed, depending on bicycle, roadway, and travel attributes that determine energy state changes and losses.

The focus of this study is variation in bicyclist ventilation during riding. Hence, subject-specific variables are assumed constant over the course of a trip and grouped into a “Subject”

¹ This paper uses physiological definitions whereby “ventilation” is the process of moving air into and out of the lungs while “respiration” is the exchange of gases which takes place in the lungs.

factor. Then the connection between ventilation and travel conditions can be made in two steps: 1) estimate energy transferred to the bicycle, based on travel and roadway conditions, and 2) model ventilation as a function of energy transferred to the bicycle, mediated by the subject. The objectives of this paper are to:

1. Describe and validate a new approach to measure on-road ventilation rate using an unobtrusive and economical chest strap, and
2. Analyze the dynamic ventilatory response to power output while bicycling, as determined by roadway and travel conditions.

The goal of this research is to provide a clearer and more quantitative understanding of on-road ventilation and power output for urban bicyclists. Quantifying the relationship between on-road ventilation and travel conditions (road grade, speed, acceleration, etc.) will be useful for future studies of pollutant inhalation by bicyclists as well as studies of energy expenditure and physical activity.

METHOD

Data collection

On-road data were collected in Portland, Oregon on nine days between October 2012 and September 2013. Approximately 55 person-hours of data were collected, with each subject riding 2-4 hours per day participated. All data were collected near the morning peak period (7-10am). A variety of roadway facilities were included in prescribed routes, including off-street bicycle/pedestrian paths and mixed-use roadways ranging from local roads to major arterials. The study subjects were volunteers instructed to adhere to safe riding practices, follow traffic laws, and ride at a pace and exertion level typical for utilitarian travel (i.e. commuting).

Three subjects participated in the data collection; this was considered adequate because the primary focus of the study involved travel covariates rather than inter-subject covariates. The subjects were recruited from the university student body². All subjects were nonsmokers who reported moderate regular physical activity and good respiratory health based on the American Thoracic Society respiratory disease questionnaire³. The characteristics of subjects A, B, and C were (respectively): male, male, and female; age, 34, 28, and 45; average bicycle weight (including all gear), 25, 22, and 23 kg; and average post-ride body weight, 80, 70, and 75 kg.

GPS receivers recorded 1 Hz location data with time stamps. Redundant GPS devices and simultaneous on-bicycle video were used to cross-check the location data for reliability. Meteorological variables were also measured for context. Temperature and humidity were measured on-road with a HOBO U12 data logger attached to the bicycle. Wind data were retrieved from an Oregon Department of Environmental Quality monitoring station in the data collection area (Station SEL 10139).

In order to calculate grade, elevation was extracted from archived data (1 m digital elevation maps based on LIDAR) and differentiated in two dimensions. Grade of travel (G) was calculated as $G = \frac{\Delta \text{elevation}}{\text{distance}} 100\%$ using 1 Hz elevation and location data. Grades over 25% or under -25% were removed (0.3% of grade data), and a smoothing algorithm was applied (five-second moving average).

² Approval for the research was obtained from Portland State University's Human Subjects Research Review Committee (HSRRC).

³ American Thoracic Society, 1979. "Recommended Respiratory Disease Questionnaires for Use with Adults and Children in Epidemiological Research."

Physiology monitoring

Heart rate and breathing rate were measured by a physiology (ventilation and heart rate) monitoring strap worn around the bicyclist's chest (BioHarness 3, Zephyr, Annapolis, MD). The BioHarness 3 is a relatively new commercial device for mobile physiological monitoring. Data are logged at 1 Hz and a custom Android application was written to log the BioHarness data stream with simultaneous GPS data on a smartphone⁴.

The BioHarness band stretches around the chest and contains a conductive elastic fabric. Expansion of the chest is monitored by measuring the resistance in the conductive fabric. The breathing rate (f_b) is assessed by detecting inflections in the resistance waveform. The BioHarness also reports a raw breath amplitude (B_A) value in volts which is "indicative". Because the measured resistance changes with the expansion of the chest, there should be a relationship between breath amplitude B_A and the tidal volume V_T . However, the relationship between B_A and V_T will likely depend on the location and tightness of the strap. By calibrating B_A to V_T each time the BioHarness was used, session-specific $B_A \sim V_T$ relationships were estimated and used to calculate dynamic V_E from on-road measured f_b and B_A (see next subsection). The BioHarness data fields used in this research were:

1. Heart rate, HR (from ECG sensors)
2. Heart rate confidence (in %)
3. Breathing rate, f_b
4. Breathing amplitude, B_A

Tidal volume calibration

A tidal volume calibration was conducted by each subject at the beginning and end of each data collection period. The tidal volume calibration consisted of 30-60 seconds of steady ventilation at prescribed tidal volumes of 500, 1000, 1500, and 2000 mL. An incentive spirometer was provided to the subjects to monitor tidal volume (DHD222500, Medline, Mundelein, Illinois). The first ten seconds of B_A readings at each tidal volume were discarded, and the remaining B_A values averaged for each tidal volume. A curve was fit to each set of calibration data using the equation $V_T = a + b \cdot B_A$. Calibration periods with missing data or a statistical fit of $R^2 < 0.75$ were discarded (4 calibration periods with poorly fitted straps or inconsistent tidal volumes). Median coefficients for the calibration curves were $a = -0.5702$ and $b = 16.454$ (V_T in L and B_A in mV).

On-road V_T was estimated from B_A measurements by applying the calibration curve $V_T = a + b \cdot B_A$ with calibration parameters a and b interpolated between the before and after calibration periods for each data collection. Data collections without calibration data at one end (before or after) used a single set of calibration parameters. Minute ventilation was then calculated $\dot{V}_E = V_T f_b$. Observations were filtered with the following constraints:

- BioHarness reported HR confidence value of $\geq 80\%$
- B_A values within the range of calibration data
- $1 < f_b < 100$
- $20 < HR < 200$

50,241 observations (23%) did not meet these constraints or were missing data. The processed physiological data set included 165,473 one-second data points (46 hours).

⁴ See <http://alexbigazzi.com/PortlandAce>

Ergometer testing

Physiological attributes of the subjects were assessed with a standard bicycle ergometer exercise test (4). Tests were conducted on bicycle ergometers (New Bike Exc 700, Technogym, Gambettola, Italy) on September 12, 2013. The protocol was 3-minute incremental power output of 50 W from 0 W to volitional exhaustion – which was 350, 250, and 200 W for subjects A, B, and C, respectively. Self-selected cadences were around 70 rpm.

Physical model of bicyclist power output

A first-principles physical model was used to estimate bicyclist power output from measured roadway and travel characteristics. Olds (9) provides a review of bicycle energy and power models. Beyond accounting for changes in energy state due to speed and elevation, almost all power demand models include aerodynamic drag and rolling resistance terms. Some models include other factors in varying level of detail, such as angular momentum of the wheels and the rider's limbs, spoke drag, turbulence around the pedals, rolling resistance sensitivity to grade, and varying air density (10–15).

The energy state of a bicycle/rider system is the sum of its potential energy (PE) and kinetic energy (KE). The energy flux balance for the bicycle + rider system is

$$W_M - W_L - W_B = \Delta KE + \Delta PE \quad 1$$

where W_M is the mechanical work input from the bicyclist⁵, W_B is energy dissipated through braking (as heat), W_L is other energy lost through drag, rolling resistance, friction, etc., and ΔKE and ΔPE are the changes in kinetic and potential energy. W_M and W_B are difficult to measure directly and unavailable in the study data set; KE and PE can be estimated from speed, weight, and elevation data, and W_L can be estimated from the literature with the assumption of certain parameters.

We define the net work on the bicycle + rider system as $W_N = W_M - W_B$. The assumptions

1. $W_B \geq 0$ (i.e. brakes only remove energy from the system),
2. $W_M \geq 0$ (i.e. the bicyclist can only input energy to the system⁶), and
3. $W_M = 0 \mid W_B = 0$ (i.e. the bicyclist is never pedaling and braking at the same time)

then lead to

$$W_M = \begin{cases} W_N & W_N > 0 \\ 0 & W_N \leq 0 \end{cases} \quad 2$$

Additionally, $W_B = W_N$ when $W_N \leq 0$ and $W_B = 0$ otherwise. With work in units of energy, the time rates of work and energy transfer are in units of power (e.g. watts). From the bicycle energy literature (12), neglecting spoke drag, rotational inertia of the wheels, and bearing losses, and assuming relatively low wind speeds and grades, energy transfer rates are:

⁵ W_M is not the same as the total external work generated by the bicyclist W_h , which can be related to W_M by $W_h = \frac{W_M}{\eta}$, where η is the efficiency of power transfer to the bicycle powertrain (including losses in the drivetrain and energy used for upper body control). In the ventilation ~ power modelling below, the efficiency factor η would be included in the subject-specific model coefficients.

⁶ This might not be true for fixed-gear bicycles.

$$\frac{\Delta KE}{\Delta t} = \frac{m_T \Delta v_b^2}{2 \Delta t}$$

$$\frac{\Delta PE}{\Delta t} = v_b m_T g G$$

$$\frac{W_L}{\Delta t} = \frac{1}{2} \rho C_D A_F v_b^3 + v_b C_R m_T g$$

where the variables are defined:

- m_T , the total mass of the bicycle + rider system
- v_b , the ground speed of the bicyclist
- g , the acceleration due to gravity
- G , the grade of travel
- ρ , the air density
- C_D , the drag coefficient
- A_F , the frontal area of the bicyclist (assuming 0 yaw angle)
- C_R , the coefficient of rolling resistance

A modified drag coefficient is defined: $C'_D = \frac{1}{2} \rho C_D A_F$, leading to a rate of net work of

$$\dot{W}_N = \frac{W_N}{\Delta t} = \frac{\Delta KE + \Delta PE + W_L}{\Delta t}$$

$$\dot{W}_N = \frac{m_T \Delta v_b^2}{2 \Delta t} + v_b m_T g G + C'_D v_b^3 + v_b C_R m_T g \quad 3$$

All of the parameters needed to calculate \dot{W}_N are measured in the study data set except C'_D and C_R , for which there is information in the literature.

Table 1 shows power output parameters applied for the three study subjects, including measured values and estimates informed by the literature. All three subjects had 700c “commuter” style (semi-slick) tires, 25-28mm. Subjects A and B rode touring bicycles, while subject C rode a more upright city bicycle. All three subjects rode with rear panniers, though subject A also had a large trunk box holding sample bags and air sampling equipment mounted in a front basket. These additions would increase both the frontal area and drag coefficient for subject A. All three subjects rode in “touring” or “upright” positions. The values in the following table for the unmeasured parameters are estimates from several sources in the literature, especially Olds et al. (13) and Wilson (15).

Power output or rate of work estimates ($\dot{W}_M = \frac{W_M}{\Delta t}$) were made for each subject using Equations 2 and 3 with on-road speed and grade data and the parameters in Table 1. \dot{W}_M was constrained to the maximum power output from ergometer testing in Table 1. Power output was also calculated in units of MET. A MET is a standardized unit of metabolic energy expenditure that is normalized to body mass and resting metabolic rate. Resting activities are at a MET of 1. “Standard MET” values are calculated with respect to a resting metabolic rate of 3.5 mL O₂ per

minute, per kg body mass. The American College of Sports Medicine (ACSM) equation⁷ for oxygen consumption during bicycling (in mL O₂ per kg per min) is:

$$\dot{V}_{O_2} = 10.8 \frac{\dot{W}_M}{m_r} + 7$$

with \dot{W}_M in W and m_r (body mass) in kg (16). Standard MET can then be calculated as

$$MET = \frac{\dot{V}_{O_2}}{3.5} = 3.09 \frac{\dot{W}_M}{m_r} + 2 .$$

RESULTS

Summary statistics for physiology and power output data are shown in Table 2 using five-second aggregated data. Ventilation volumes are presented at ambient temperature and pressure, which allows direct application for inhalation rate estimates. Mean ventilation rate of 22.4 lpm (liters per minute) is in good agreement with past studies of bicyclist inhalation (2). The average sampling conditions were 17 kph travel speed (without stops), 19 °C (range: 11-25 °C), 75% relative humidity (range: 57-91%), and 1.8 mps wind speed (range: 0.6-3.6 mps).

The calculated MET values agree well with published research. The Compendium of Physical Activity lists 16 different types of bicycling as activities with assumed static energy expenditures ranging from 3.5 MET for “leisure” bicycling at 5.5 mph to 16 MET for competitive mountain bicycle racing (17). “General” bicycling is at a MET of 7.5 and bicycling “to/from work, self selected pace” is at a MET of 6.8 in the Compendium. Other research has reported typical non-racing bicyclist MET of 5-7 (14, 18, 19).

Ventilation and heart rate

The lagged covariance between ventilation and heart rate was calculated using 1-second data. The covariance peaks at 20 seconds, indicating that heart rate changes lead ventilation changes by around 20 seconds. This lag is relevant to consider for research designs that use on-road measured *HR* to predict dynamic ventilation rates.

The relationship between ventilation and heart rate was modeled as

$$\ln(\dot{V}_E)_i = \alpha + \beta \cdot HR_{i-4}$$

using five-second data, where HR_{i-4} is heart rate lagged by four periods (4 lags = 20 seconds) and α and β are fit parameters. Pooled and subject-segmented OLS models were estimated with Newey-West HAC (heteroscedasticity and autocorrelation consistent) robust standard error estimates. The estimated model results by subject and pooled are shown in Table 3. All coefficients are significant at $p < 0.01$. Due to serial correlation, using un-lagged heart rate (HR_i) as the independent variable generates similar models but with higher standard errors.

The estimated β coefficients in Table 3 are in line with the literature, which suggests central values of 0.016-0.023 for bicyclist $\ln \dot{V}_E \sim HR$ slope coefficients, heterogeneous to individuals (1, 18, 20, 21). Mermier et al. (8) report slopes ranging from 0.016 to 0.029 for 15 healthy men who performed maximum exercise tests on ergometers. The ventilation-heart rate models provide validation support for the BioHarness-based estimation of on-road ventilation. The model fits (R^2) in Table 3 are lower than past reported values from lab ergometer studies (1, 8), which is attributable to greater measurement error in the indirect field measurements of

⁷ <http://certification.acsm.org/metabolic-calcs>

ventilation rate (using the BioHarness chest strap with spirometer calibrations) than the direct laboratory measurements of ventilation rate (using facemasks and pneumotachometers).

Power Analysis

The application of the power equations allows the power demands on the bicyclists to be broken down by terms. The net energy attributable to each power term was:

- Kinetic energy flux (ΔKE): 0 kW,
- Potential energy flux (ΔPE): -155 kW (net elevation loss),
- Aerodynamic drag loss: 1,792 kW, and
- Rolling resistance loss: 403 kW.

Cumulative wattage by power equation term was also calculated for observations with complete power data (some observations were missing grade data, so the ΔPE term was *NA*). Of the 39,508 five-second periods in the data set, 21,963 had complete power data, with total energy expenditure of the riders of 3,908 kW. This energy (plus the input of 155 kW of *PE*) was dissipated as 43.5% aerodynamic drag, 9.7% rolling resistance, and 46.8% braking.

The bicyclists were performing pedaling work ($W_N > 0$) for 14,978 (68%) of the complete observations (20.8 hours). Isolating those periods when the riders were pedaling, the individual sums of energy for the other terms of the power equation were 54.5% kinetic energy, 2.2% potential energy, 35.7% aerodynamic drag, and 7.7% rolling resistance. In other words, when pedaling, 43% of the energy input was immediately dissipated as drag and rolling losses (maintaining speed) and the other 57% went to useable, recoverable energy (primarily as speed, but also as elevation).

Ventilation and power output

Lagged covariance between \dot{W}_M and *HR* and between \dot{W}_M and \dot{V}_E was calculated using five-second aggregated data (a five-second moving average was used to estimate grades). Covariance between \dot{W}_M and *HR* peaks at one lag (5 seconds), and covariance between \dot{W}_M and \dot{V}_E peaks at six lags (30 seconds). Thus, the physiological response to increased power output is fast in heart rate and slower in ventilation. Again, this is relevant for study designs where ventilation is not measured directly but estimated from heart rate or power output.

An unconstrained distributed lag model of ventilation on power output was specified out to 30 lags (2.5 min):

$$\ln(\dot{V}_E)_t = \alpha + \sum_{i=0}^{30} \beta_i \dot{W}_{M,t-i} + \varepsilon_t$$

with \dot{V}_E in lpm, \dot{W}_M in W, and ε_t an i.i.d. error term. Longer lags were explored but found to be not significant. The model was estimated separately for each subject, with Newey-West HAC robust standard error estimates. The cumulative effect of \dot{W}_M on \dot{V}_E is represented by $\beta_T = \sum_{i=0}^{30} \beta_i$.

Estimated subject-specific and pooled model results are shown in Table 4. As in Table 3, low R^2 values are attributable to measurement error in the indirect field measurements of ventilation rate, in addition to estimated energy transfer rates. The left plot in Figure 2 shows the marginal impact of \dot{W}_M on \dot{V}_E as $\beta_i \cdot 100\%$ (versus lag in seconds, $5i$). The right plot in Figure 2 shows the cumulative lagged impact of \dot{W}_M on \dot{V}_E , calculated at lag L as $\frac{\sum_{i=0}^L \beta_i}{\beta_T} \cdot 100\%$.

The plots in Figure 2 show that the majority of the effect of power output on ventilation is realized within the first minute. The mean lag (the time period at which half of the effect of \dot{W}_M on \dot{V}_E is achieved, computed $\frac{\sum_{i=0}^{30} i \cdot \beta_i}{\beta_T}$) was 0.56-0.85 min for individual subjects and 0.78 min in the pooled model. The median lag (the lag at which $\frac{\sum_{i=0}^L \beta_i}{\beta_T} \approx 0.5$) was 0.58-0.83 min for individual subjects and 0.75 min in the pooled model. The lag values compare well with previous studies that found around 50% adaptation of ventilation to exercise after the first minute, with some inter-subject variability (22, 23).

Figure 3 illustrates the sensitivity of the $\dot{V}_E \sim \dot{W}_M$ relationship to the energy equation parameters C'_D and C_R . The 3 plots in Figure 3 show modeled β_T as shadings over a wide range of values for C'_D and C_R , for each subject. Note the different color scales in each figure, centered near the β_T estimate in Table 4. The selected ranges for C'_D and C_R are based on the literature used in Table 1 (12, 15). The $\dot{V}_E \sim \dot{W}_M$ relationship is more sensitive to C'_D than C_R . Higher values of these power equation parameters increase estimates of on-road \dot{W}_M and so reduce the size of β_T . The modeled β_T is within 0.001 of the initial estimate over a wide range of parameter values.

Comparison with theory

The β_T values in Table 4 are consistent with expectations from physiology. Oxygen demand (\dot{V}_{O_2}) increases with power output at around 10-12 mL O₂/min per W (4, 9, 24–26)⁸. This slope reflects a unit conversion of 1W = 2.86 ml O₂/min and a human mechanical cycling efficiency⁹ of ~25% (3, 15, 27).

The relationship between V_E and \dot{V}_{O_2} has been modeled as both linear and exponential, with better fits over a wide range of \dot{V}_{O_2} using exponential forms. The exponential form, $\ln \dot{V}_E \sim \dot{V}_{O_2}$, has been estimated with a slope of around 1.2 (28–30)¹⁰. In linear form, the ventilatory equivalent for oxygen (\dot{V}_E/\dot{V}_{O_2}) during moderate exercise is around 20-30 (31–33). Assuming a linear ventilatory equivalent of 25 (34), at ventilation rates of 20-50 lpm during exercise the semi-elasticity of \dot{V}_E to \dot{V}_{O_2} (i.e. the slope of $\ln \dot{V}_E \sim \dot{V}_{O_2}$) would be expected to be around 0.5-1.3.

The slope of $\ln \dot{V}_E \sim \dot{V}_{O_2}$ can be converted to $\ln \dot{V}_E \sim \dot{W}_M$ using the factor 0.01 (LO₂/min/W), resulting in expected $\ln \dot{V}_E \sim \dot{W}_M$ slopes of roughly 0.005-0.013. Thus, the modeled values of β_T in Table 4 and the sensitivity ranges in Figure 3 are in the range of expected ventilation response to power output. The theoretical values are based on steady-state relationships and ergometer testing protocols used in physiology studies. Low-ranged values of the $\ln \dot{V}_E \sim \dot{W}_M$ slope in these data could be attributed to a muted ventilatory response to *dynamic* power output.

⁸ Zoladz et al. (26) found that \dot{V}_{O_2} increases non-linearly at power output over 250W

⁹ the amount of energy derived from atmospheric oxygen that is translated to external work, previously defined as η

¹⁰ A common model uses the oxygen uptake efficiency slope (OUES), which is defined as

$$\dot{V}_{O_2} = OUES \cdot \log_{10} \dot{V}_E + \mu.$$

OUES can be converted to a $\ln \dot{V}_E \sim \dot{V}_{O_2}$ slope coefficient by calculating $\frac{\ln 10}{OUES}$. Typical OUES values are around 1.8-2, increasing with cardiac fitness.

For a body mass of 75 kg, standard MET increases at 0.04 per watt \dot{W}_M (see Section 2.5). Thus, the expected $\ln \dot{V}_E \sim \dot{W}_M$ slopes can be converted to expected $\ln \dot{V}_E \sim MET$ slopes of 0.1-0.3. In linear form, ventilatory equivalents for oxygen (\dot{V}_E/\dot{V}_{O_2}) of 20-30 can be converted to expected $\dot{V}_E \sim MET$ slopes of 5.7-8.6. Ventilation vs. MET relationships were estimated using 60-minute aggregated data ($N = 47$). A regression of $\ln \dot{V}_E$ on MET generates a slope coefficient of 0.22 ($p < 0.01$, $R^2 = 0.16$) and a regression of \dot{V}_E on MET generates a slope coefficient of 6.5 ($p < 0.01$, $R^2 = 0.27$) – both well in line with expectations.

The ventilation vs. power relationships are expected to vary some with personal characteristics. The ventilatory equivalent for oxygen \dot{V}_E/\dot{V}_{O_2} (and in turn the slope of $\dot{V}_E \sim \dot{W}_M$) tends to increase with pulmonary or cardiovascular diseases, be higher in children and adolescents than adults, and decrease with aerobic training (4, 34, 35). Hence, a broader population of bicyclists including children and adults with respiratory diseases could have higher $\dot{V}_E \sim \dot{W}_M$ slope coefficients than estimated in this study. But power output would also likely vary, and a population-wide analysis of bicyclist ventilation would have to consider both aspects jointly.

Comparison with ergometer testing and direct power measurements

The $\ln \dot{V}_E \sim \dot{W}_M$ relationship was estimated for the same subjects using ergometer test data. A model was specified $\ln(\dot{V}_E) = \gamma + \lambda \dot{W}_M$ for each subject, with \dot{V}_E in lpm, \dot{W}_M in W, and parameters γ and λ . Subject-specific and pooled models were estimated using OLS with Newey-West HAC standard errors for data aggregated at each power output level from the ergometer test. Model estimation results are shown in Table 5. All coefficients were significant at $p < 0.01$.

The parameter estimates in Table 5 are also in range of expectation from theory, and compare reasonably well with the slope parameters from on-road data shown Table 4. The pooled model is nearly the same. In both the on-road and ergometer models, Subject B has higher baseline ventilation, but less ventilatory response to power output than the other subjects. Subject C has the highest ventilatory response to power output. Subjects B and C both showed stronger ventilatory responses to power output in ergometer testing than on-road, while the opposite occurred for subject A. Differences between ergometer and on-road testing could be due to static vs. dynamic power output and/or errors in assumed bicycle power equation parameters (Figure 3).

The bicycle for Subject A was equipped with a PowerTap (Madison, Wisconsin) G3 Hub capable of measuring power transfer to the rear wheel. The ventilation vs. power relationship was estimated using this smaller set of directly-measured power data with the distributed lag model specification, yielding coefficient estimates of $\alpha = 2.564$ and $\beta_T = 0.00662$, with a mean lag of 0.75 minutes ($N = 7,626$, adjusted R^2 of 0.25). The consistency of these parameters with the previous results using modeled power output provides additional validation of the study findings.

CONCLUSIONS

Physiology monitoring straps provide an unobtrusive way to measure ventilation rates for bicyclists. Monitoring straps that measure breathing can be purchased for a small fraction of the cost of a portable facemask system, are less cumbersome for participants, and enable concurrent measurement of ventilation and uptake doses. Indeed, this study is part of a larger research project that simultaneously measures ventilation and breath biomarkers of VOC uptake for urban bicyclists. Ventilation rate measurements were validated by heart rate vs. ventilation rate

relationships in this paper. Future work should further validate this method by direct comparison with portable facemask systems.

Average ventilation rate and power output in this study were 22 lpm and 126 W (MET of 7.0), in agreement with past studies of commuting bicyclists. The on-road ventilatory response to dynamic power output was 0.4-0.8 % per W, slightly lower than from ergometer testing for the same subjects and at the low end of expected values from physiology literature. This quantification allows ventilation to be estimated directly from travel conditions (road grade, speed, etc.) and a few key bicyclist parameters (mass and coefficients of rolling resistance and aerodynamic drag), or from power output measurements generated by power meters in the rear hub, crank, or pedals.

On-road ventilation lagged heart rate by 20 seconds and lagged power output by 50 seconds. The ventilation lag of heart rate is important to consider for study designs using only heart rate monitors to estimate dynamic on-road ventilation. The ventilation lag of power output implies that ventilatory responses are not coincident with locations of energy expenditure, but spread out over 1-2 minutes. Assuming bicycling speeds around 15 kph, a lag of 50 sec is equivalent to a spatial difference of 200 m. This spatial lag in the ventilatory response is a potentially important consideration for pollutant inhalation “hot spots”. Exposure concentrations are expected to be elevated near intersections; power output, too, is high during an acceleration from a stop at an intersection – but the ventilatory response is spread out over several blocks. Conversely, when bicyclists are stopped at an intersection with a power output of 0 W, they are breathing with the residual influence of the past 2 minutes of exertion.

In this study 47% of on-road energy loss was due to braking and 44% due to aerodynamic drag. A more naturalistic bicycle travel data set would be needed to estimate a more representative distribution of power demands for urban bicycling. Future work will explore the influence of travel attributes on power output and ventilation in more detail, including the relative effects of stops, grades, and travel speeds, and power/speed trade-offs for total ventilation per unit distance or per trip. This paper is an important step toward quantifying the impact travel characteristics on bicyclists’ pollutant inhalation risks.

ACKNOWLEDGMENT

This research was supported by the National Institute for Transportation and Communities (NITC), Portland Metro, and the City of Portland. Alexander Bigazzi is supported by fellowships from the U.S. National Science Foundation (Grant No. DGE-1057604) and NITC.

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Table 1. Parameters used in calculating bicyclist power

| | <i>Subject A</i> | <i>Subject B</i> | <i>Subject C</i> | <i>Source</i> |
|---|----------------------|----------------------|----------------------|--|
| m_r (kg) | 80 | 70 | 75 | Measured; mass of the rider |
| m_T (kg) | 105 | 91 | 97 | Measured; includes rider and bicycle |
| Height, H (cm) | 189 | 175 | 163 | Measured; standing |
| Surface area of rider, A_S (m ²) | 2.32 | 2.07 | 2.02 | Olds et al. (13); $A_S = H^{0.725} m_T^{0.425} 0.007184$ |
| Frontal area of rider, A_{Fr} (m ²) | 0.59 | 0.51 | 0.49 | Olds et al. (13); $A_{Fr} = 0.3176 A_S - 0.1478$ |
| Frontal area of bicycle, A_{Fb} (m ²) | 0.12 | 0.12 | 0.12 | Olds et al. (13) |
| Frontal area inflation factor, F | 1.2 | 1.1 | 1.1 | Assumed; loose clothing, upright position, panniers, and equipment |
| Total frontal area, A_F (m ²) | 0.85 | 0.69 | 0.67 | $A_F = F(A_{Fr} + A_{Fb})$ |
| C_D | 1.1 | 1.0 | 1.0 | Wilson (15) |
| ρ (kg/m ³) | 1.23 | 1.23 | 1.23 | Assumed; sea level, 15°C |
| C'_D | 0.6 | 0.4 | 0.4 | $C'_D = \frac{1}{2} \rho C_D A_F$ |
| C_R | 0.004 | 0.004 | 0.004 | Wilson (15) |
| Maximum power output (W) | 300 | 250 | 200 | Ergometer testing; < 3 minutes |

Table 2. Summary statistics for physiology and power output data (five-second aggregation)

| | <i>Units</i> | <i>Min</i> | <i>1st Quartile</i> | <i>Median</i> | <i>Mean</i> | <i>3rd Quartile</i> | <i>Max</i> | <i>N</i> |
|----------------------|---------------------|------------|--------------------------------|---------------|-------------|--------------------------------|------------|----------|
| <i>HR</i> | min ⁻¹ | 20 | 69 | 81 | 84 | 96 | 200 | 39,508 |
| <i>f_b</i> | min ⁻¹ | 2 | 16 | 22 | 22 | 28 | 51 | 39,508 |
| <i>B_A</i> | mV | 24 | 61 | 85 | 92 | 116 | 280 | 38,675 |
| <i>V_T</i> | mL | 0 | 600 | 889 | 1002 | 1275 | 7238 | 32,471 |
| <i>V_E</i> | l min ⁻¹ | 0.0 | 10.3 | 18.0 | 22.4 | 29.7 | 165.6 | 32,471 |
| <i>W_M</i> | | | | | | | | |
| Pooled | W | 0 | 0 | 114 | 126 | 235 | 300 | 21,963 |
| Subject A | W | 0 | 0 | 126 | 135 | 265 | 300 | 16,950 |
| Subject B | W | 0 | 0 | 73 | 101 | 207 | 250 | 2,555 |
| Subject C | W | 0 | 0 | 74 | 90 | 200 | 200 | 2,458 |
| <i>MET</i> | | | | | | | | |
| Pooled | MET | 2.0 | 2.0 | 6.5 | 7.0 | 11.2 | 13.6 | 21,963 |
| Subject A | MET | 2.0 | 2.0 | 6.8 | 7.2 | 12.2 | 13.6 | 16,950 |
| Subject B | MET | 2.0 | 2.0 | 5.2 | 6.4 | 11.1 | 13.0 | 2,555 |
| Subject C | MET | 2.0 | 2.0 | 5.0 | 5.7 | 10.2 | 10.2 | 2,458 |

Table 3. Model parameters relating ventilation to heart rate

| | <i>Subject A</i> | <i>Subject B</i> | <i>Subject C</i> | <i>Pooled</i> |
|----------|------------------|------------------|------------------|---------------|
| α | 0.406 | 0.159 | 1.487 | 0.782 |
| β | 0.0298 | 0.0271 | 0.0156 | 0.0244 |
| N | 23,127 | 5,053 | 4,291 | 32,471 |
| R^2 | 0.371 | 0.239 | 0.151 | 0.290 |

Table 4. Distributed lag models of on-road ventilation as a function of power output

| | <i>Subject A</i> | <i>Subject B</i> | <i>Subject C</i> | <i>Pooled</i> |
|---|------------------|------------------|------------------|---------------|
| α | 2.185 | 2.674 | 2.318 | 2.348 |
| β_T | 0.00744 | 0.00417 | 0.00761 | 0.00645 |
| Number of significant lags ($p < 0.05$) | 28 | 10 | 11 | 26 |
| N | 13,044 | 2,248 | 2,156 | 17,448 |
| Adjusted R^2 | 0.154 | 0.024 | 0.111 | 0.140 |
| F-statistic | 77.36 | 2.76 | 9.72 | 92.36 |

Table 5. Model parameters relating ventilation to power output from ergometer testing

| | <i>Subject A</i> | <i>Subject B</i> | <i>Subject C</i> | <i>Pooled</i> |
|-----------|------------------|------------------|------------------|---------------|
| γ | 2.512 | 2.550 | 1.815 | 2.328 |
| λ | 0.00628 | 0.00561 | 0.01197 | 0.00728 |
| R^2 | 0.60 | 0.72 | 0.71 | 0.65 |

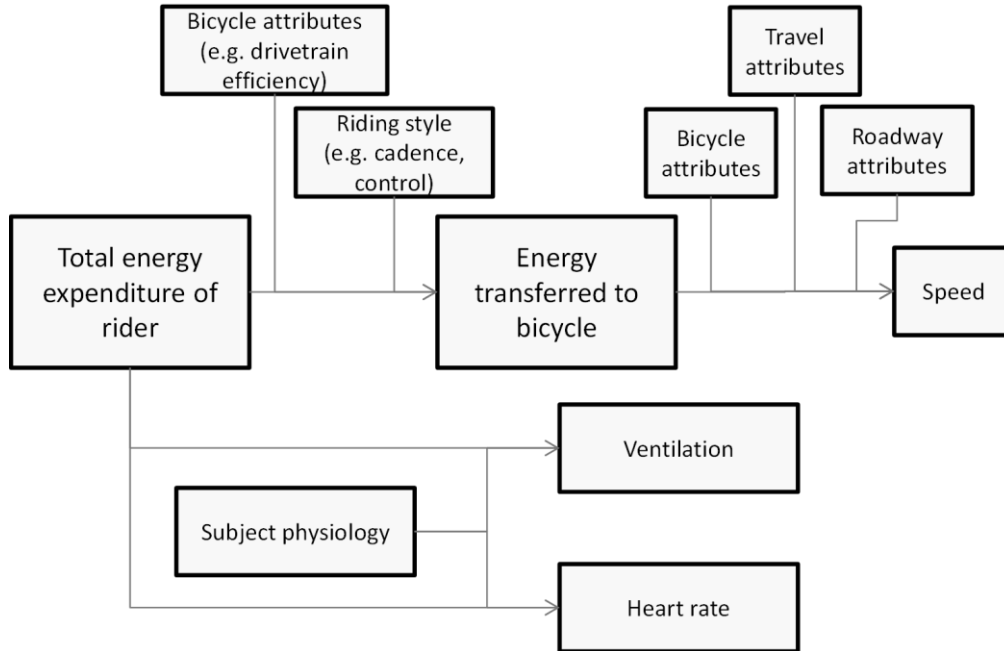


Figure 1. Conceptual diagram of the connection between bicyclist ventilation and travel conditions

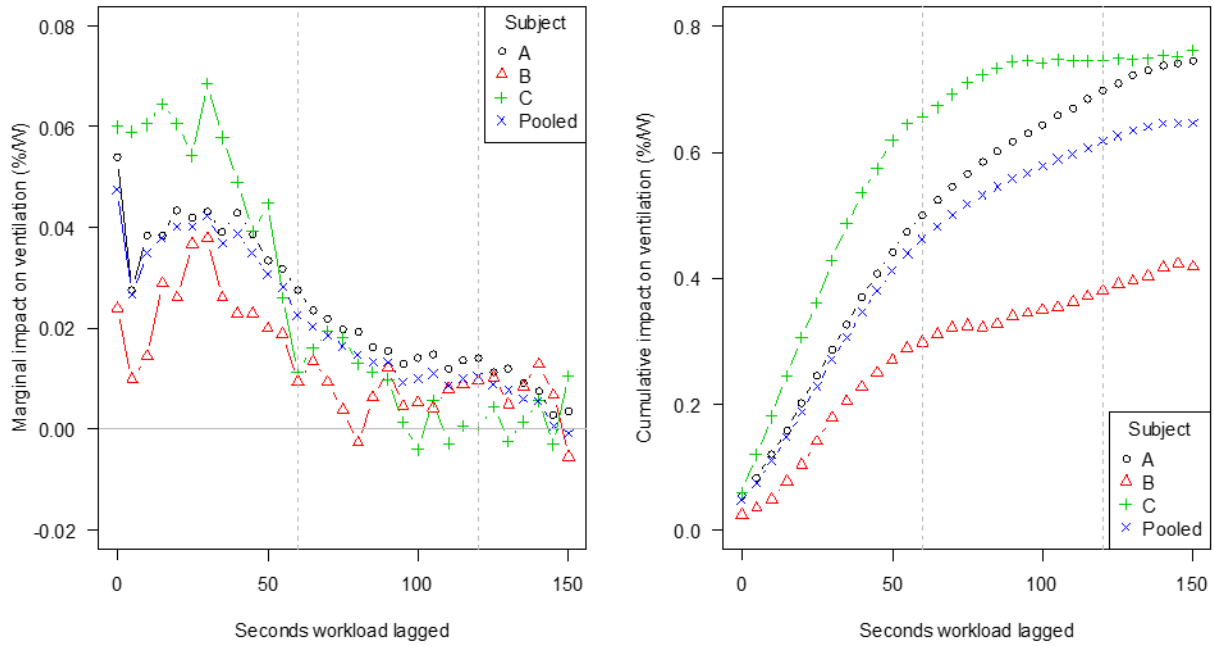


Figure 2. Marginal and cumulative impacts of power output on ventilation

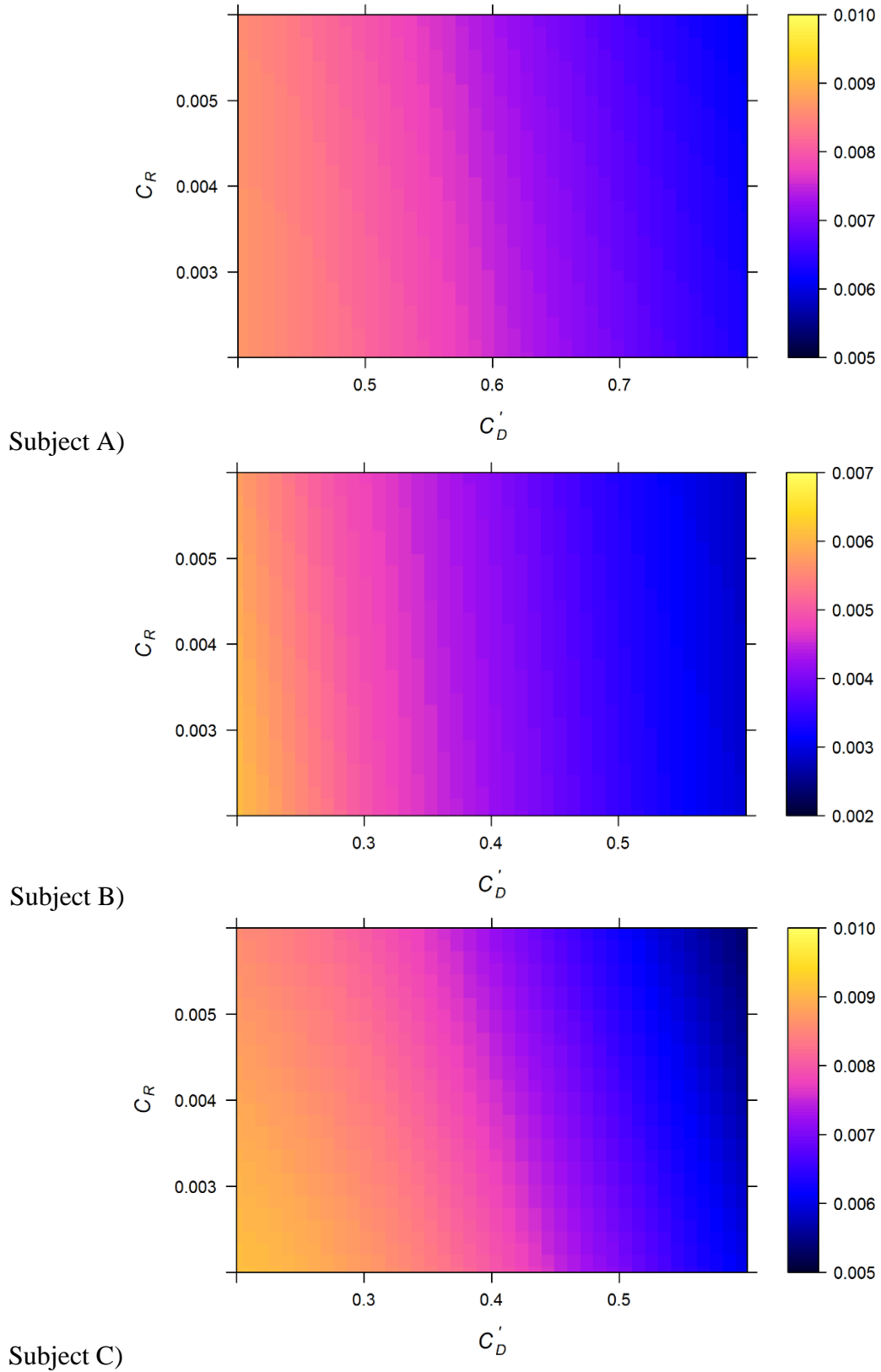


Figure 3. Sensitivity of modeled β_T to power equation parameters C'_D and C_R for each subject