Managing Commuter GHGs: Lessons and Resources for Maryland Institutions

November 6, 2013

A Presentation to the Maryland College Climate Action Workgroup

Overview

Take Home Message: Data gathering is worthwhile

Better data can improve the accuracy of GHG emissions estimates, help with the formation of mitigation strategies, and reflect policy effectiveness. This presentation and accompanying resources are designed to remove barriers to collecting/working with data as well as highlight analysis opportunities.

1. Importance of commuting in context of GHG goals
2. Overview of methods and challenges to calculation
3. The promise of data and long-term tracking
4. Brief presentation of resources and tools

Importance of Commuting

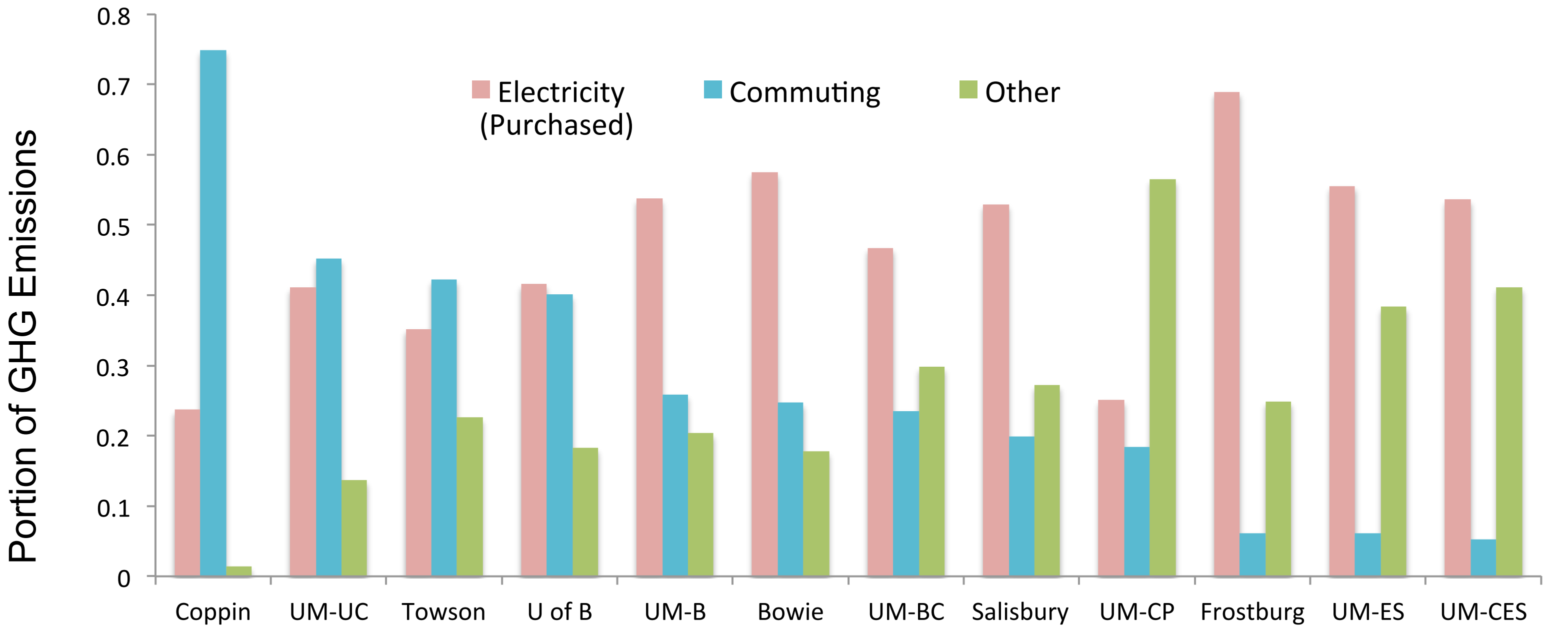

Figure. Portion of GHG emissions by source attributed to institution, ranked by commuting; ~2008 Inventory Year

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2 Overview of methods and challenges to calculation

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4 Brief presentation of resources and tools

Methods and Challenges

- The predominate method for estimating commuter emissions has been to "muddle through," or make do with limited time and resources (data, technology), and arrive at an inaccurate estimate.
- *Why not do better?* Major challenges exist:
  - Lack of regular data collection mechanisms
  - Perceived costs of collecting data, improving methods
  - Inertia in how we conduct GHG inventories

Implications

Table. Student commuter GHGs in 2007 under 2 methods for USM institution

Metric	Method 1 (Assumption-based)	Method 2 (Permit-based)
Total POV Miles Traveled	31.359 million	90.900 million
Student Commuting MTCO2e	12,797	36,853

- GHG estimates are inaccurate

- Data limitations constrain the design of mitigation strategies

E.g., What are the GHG geographic hotspots and how should that knowledge influence how we promote carpooling?

- Assumptions do not respond to mitigation strategies; activity data does

I.e., How will GHG inventories ever reflect mitigation strategies if we use and re-use assumptions instead of actual activity data?

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Opportunities: What is data worth?

- Produce more accurate GHG inventories
- Generate information about individual behavior and attitude to inform mitigation strategies
- Gain valuable feedback regarding the effectiveness of mitigation strategies
- Improve existing services

Data Collection Mechanisms
Parking permit censuses
Campus-wide transportation surveys
Car or bike counts

Behavior Modification

Feedback and Infographics:

Overview

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Resources - Survey Tools

1 Primer on transportation surveys

- *Characteristics of a good transportation survey; suggestions for structure, content, and logistics*

2 Template for 2010 College Park Survey

- *Entire transportation survey (and codes used)*

3 Sample data applications, figures and maps

Greenhouse Gas Impact per Week by Zip Code (kg-CO2)

N

Legend

kg CO2 Per Week

1 Std. Dev. = 1300kgCO2

< -0.50 Std. Dev.

-0.50 - 0.50 Std. Dev.

0.50 - 1.5 Std. Dev.

1.5 - 2.5 Std. Dev.

> 2.5 Std. Dev.

Distance from Campus (mi.)

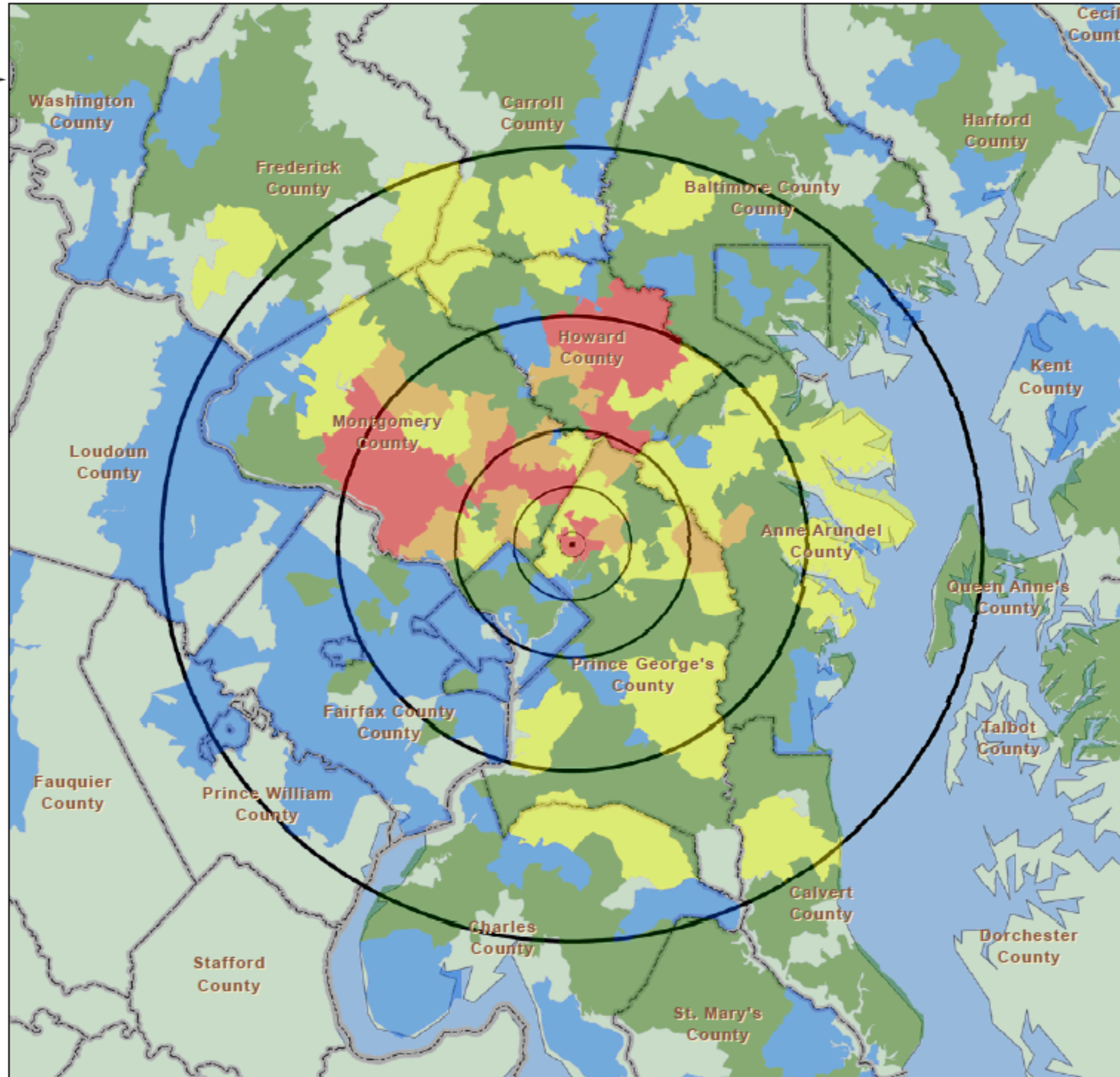
5

10

20

35

Unversity of Maryland-College Park



Zip code boundaries are from the U.S. Census 2000 Zip Code Tabulation Areas. Major Highways from SteetMap USA Permit data is from University of Maryland Deptartment of Transportation Online Permit Registration website for Fall 2009.

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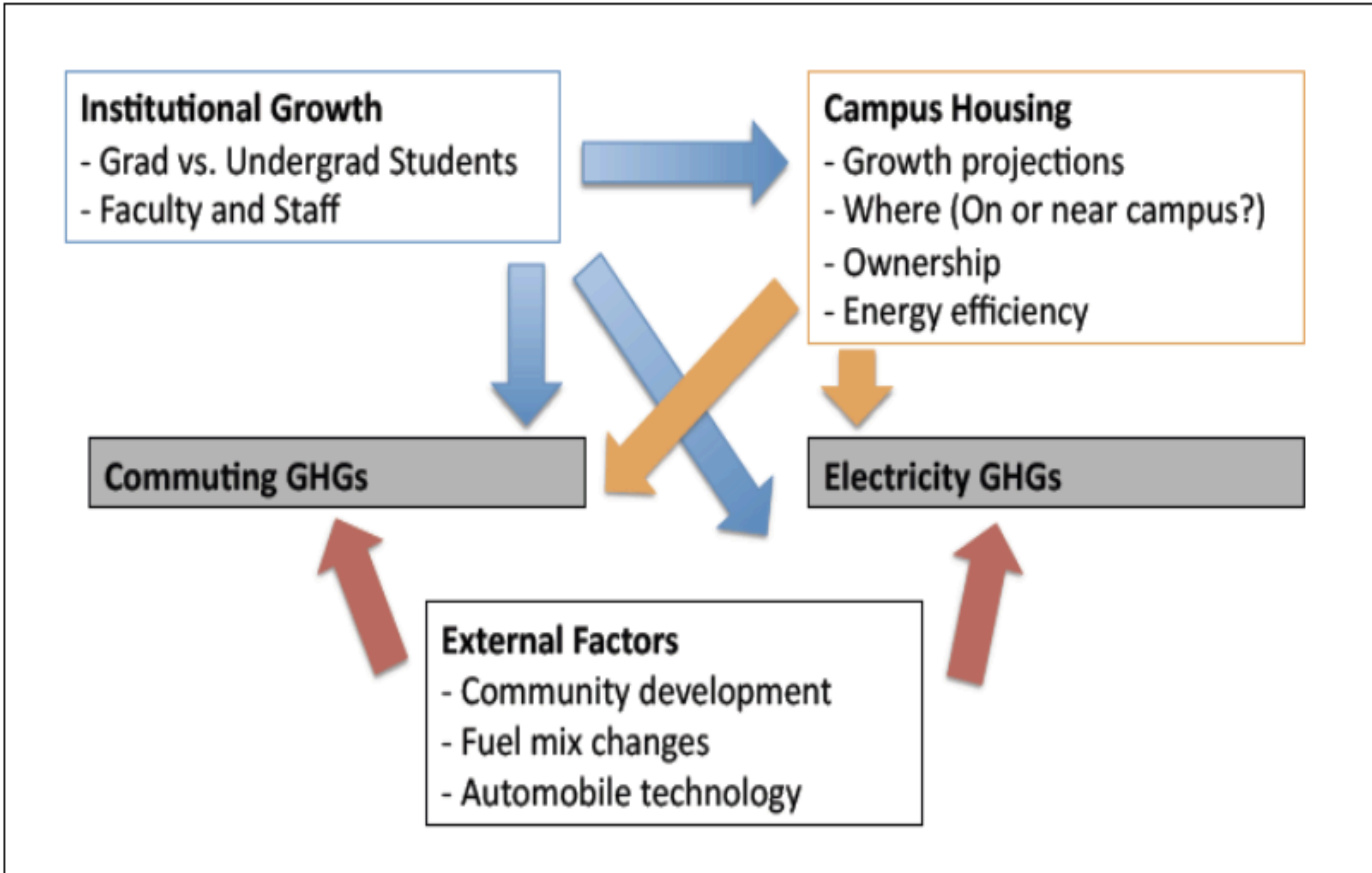
Resources - Additional

4 MS Excel File – Fuel Efficiency Lookup Table
- *With vehicle make, model and year information, the fuel efficiency of multiple vehicles can be estimated*

5 Introduction to Geographic Information Systems (GIS)
- *Short intro to the capabilities of ArcGIS and a step-by-step manual for using GIS to calculate commute distance*

6 Introduction to Systems Thinking
- *Definition of systems thinking, how it applies to higher education GHG management and a link to an online model*

Systems Thinking



Conclusion

Take Home Message: Data gathering is worthwhile

Better data can improve the accuracy of GHG emissions estimates, help with the formation of mitigation strategies, and reflect policy effectiveness. This presentation and accompanying resources are designed to remove barriers to collecting/working with data as well as highlight analysis opportunities.

Thank you

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Understanding Campus Commuting Through Data
Developed for the University System of Maryland

Created by the Center for Integrative Environmental Research (CIER) at the University of Maryland, College Park[1]

March 2012

Introduction

Lack of data is a persistent obstacle to understanding and managing campus-commuting patterns. Without commuter activity data, it is difficult to accurately estimate carbon footprints, develop customized transportation strategies, and evaluate progress towards sustainability goals.

The purpose of this document is to highlight how transportation surveys and permit applications yield valuable data that can be used to better understand commuter behavior and ultimately guide difficult greenhouse gas mitigation and sustainability decisions. Using results from the 2010 UM College Park transportation survey and the campus permit database, we present sample data applications below.

Sample data applications and analysis cover the following topics:

- Survey sample size, response rate and error;
- Commute distance distribution and mean, by employee and student;
- Distribution of arrival and departure times, by employee and student;
- Commuter mode split across multiple modes, by employee and student;
- Frequency of campus trips distribution and mean, by employee and student;
- Fuel economy descriptive statistics, by employee and student;
- Comparison of carpooling rates between full-time and part-time individuals;
- Estimate of carpool rate (i.e., number of individuals per carpool);
- Interest in carpooling as passenger and driver, by employee and student;
- Willingness to pay for vanpooling service, by employee and student;
- Ranking of common barriers and promising incentives for carpooling;
- A quick method for estimating GHG emissions with error bounds;
- Maps arranging permit numbers and estimated annual GHG emissions by zip code as well as maps demonstrating interest in carpooling;
- Predictive models for estimating commuter mode choice.

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[1] Created by Sean Williamson, CIER Faculty Research Assistant; E: srw46@umd.edu; T: 301-405-9436

What is the University's population and what was the survey sample size and error?

Table 1 Survey statistics and campus demographics

	Actual Population*	Sample Size	Percent of Pop.	Estimated Error w/ 95% confidence
Undergrad	26,922	684	2.54%	3.7%
Grad	10,719	763	7.12%	3.4%
Faculty	2,273	317	13.95%	5.1%
Staff	5,071	576	11.36%	3.8%

* Spring 2010; Data from UMD IRPA: https://www.irpa.umd.edu/

Finding – In general, the survey response from the University community was strong. The faculty sample size is small, however. Therefore, there is significant error (above 5%) associated with faculty data at the 95% confidence level. Faculty results should be understood as containing a high degree of error and future surveys should strive to boost the survey response rate for faculty members.

Where are students and employees living?

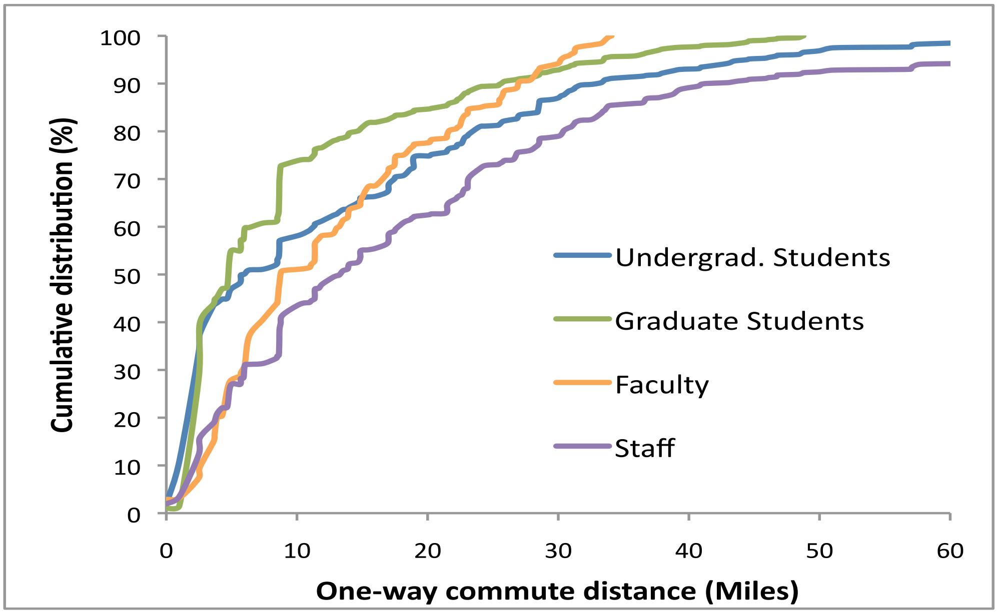

Figure 1 Cumulative distribution of one-way commute distances (miles), by classification type

Table 2 Statistics for one-way commute distance (miles), road-networked

	Mean	St. Dev	Median	Mode	Range	% less than 10 miles
Undergrad	13.44	15.36	5.96	2.48	0-113	57.34%
Grad	9.21	10.94	4.93	2.48	0-87	75.80%
Faculty	14.2	11.79	9.26	8.4	0-73	50.80%
Staff	15.62	13.44	11.38	2.48	0-82	45.53%

Finding – Approximately 40 percent of undergraduate and graduate students live within 2.5 miles (driving distance) from campus, about 35 percent of grad students live between 5-10 miles from campus, and staff typically live the furthest from campus of all community members. Among off-campus community members (i.e., commuters), grad students live the closest to campus and are good candidates for taking alternative modes of transportation to campus.

When are students and employees arriving to/departing from campus?

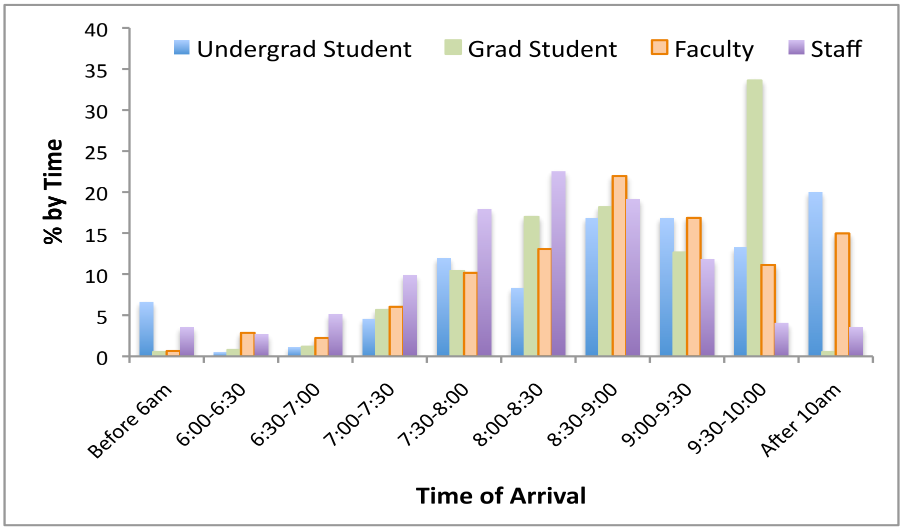

Figure 2 Campus arrival time by percentage, by class type

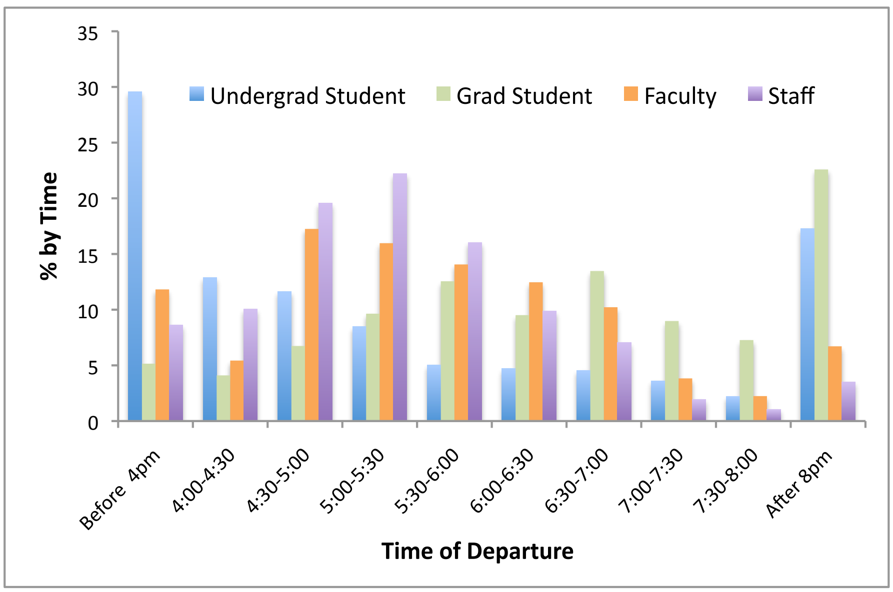

Figure 3 Campus departure time by percentage, by class type

Finding – Faculty and staff arrival and departure times are closely aligned and are fairly regular (i.e., arriving between 7-9 am and departing between 4-6 pm); students, on the other hand, have less regular schedules. Misaligned schedules suggest carpooling and vanpooling programs, as well as UMCP buses, might need to target employees and students differently.

What is the commuter mode split of the University?

Table 3 Commuter (non-residence) mode split* percentage, by class type[2]

	Bike	Walk	SOV	Carpool	Shuttle-UM	Metro Bus	Metro Rail	Mix**
Undergraduate	5.1	10.5	32.0	4.7	28.3	3.7	3.3	12.5
Graduate	5.0	8.1	25.4	4.2	22.5	2.5	2.9	29.4
Faculty	2.8	2.5	51.1	4.7	7.6	2.8	6.0	22.4
Staff	1.6	3.3	65.3	8.0	4.5	4.0	4.2	9.2

* Mode adoption defined as use of specific mode 4 days/week or more
** Mix includes individuals using modal combinations within trip, using a diversity of modes across a week, or most likely, making fewer than 4 total trips to campus per week

Finding – The dominant mode of commuting for most of the campus is single occupancy vehicles; however, the high values for the mixed mode (defined above) suggest that a significant portion of the campus has non-uniform and irregular commuting patterns (e.g., they use multiple modes, commute < 5 days/week).

Do part-time and full-time community members carpool at different rates?

Table 4 Carpool rates by all campus members, part-time and full-time only

Frequency	All (%)	Part-time (%)	Full-time (%)
Never	74.34	82.53	73.46
1/week	10.92	7.23	11.37
2/week	4.65	2.41	4.85
3/week	3.47	2.41	3.54
4/week	1.62	1.81	1.62
5/week	3.64	2.41	3.79
5+/week	1.34	1.2	1.37

Finding – Based on statistical analysis (i.e., Mann Whitney U test), the two populations ARE different in their rate of carpooling. The probability that part-time campus members carpool more than full-time campus members is just 45%.

[2] Individuals may take multiple modes to and from campus within a given week; there are also individuals that use combinations of modes to commute. One way to define an individual's commuter mode is by the number of days he or she commutes by a given mode. For example, individuals commuting 4 or more days per week by single occupancy vehicle could be defined as a single occupancy commuter. Alternative definitions could be 3 or 5 days per week or simply anyone who has a parking permit.

How often do community members come to campus per week?

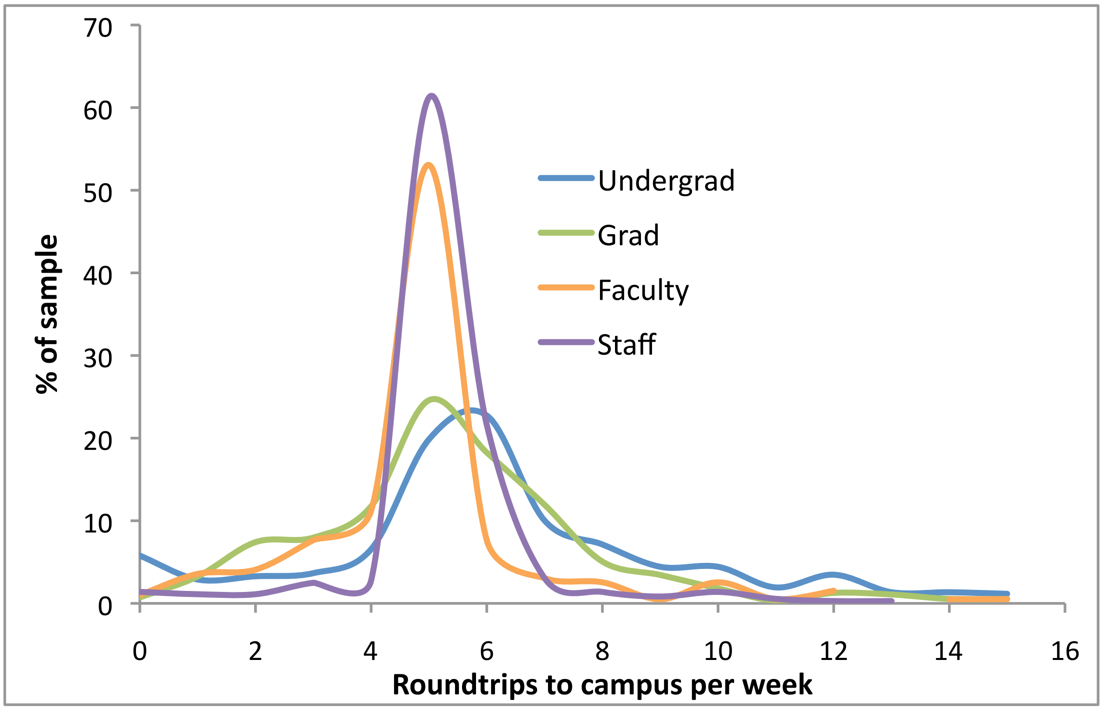

Figure 4 Distribution of roundtrips per week, by class type

Table 5 Roundtrips per week, by class type

	Mean	St. Dev.	Median	Mode
Undergraduate	6.1	3.1	6	6
Graduate	5.4	2.5	5	5
Faculty	5.0	2.2	5	5
Staff	5.3	1.6	5	5

Finding – The number of undergraduate and graduate student roundtrips to campus is more variable relative to employees. Students are likely to make more trips to campus per week than faculty or staff; this is likely a product of social and extracurricular opportunities on-campus. Undergraduate and graduate students probably expect their commuting mode to accommodate frequent and irregular (e.g., evening, weekend) trips to campus.

What is the fuel efficiency of campus vehicles by status?

Table 6 Fuel efficiency (Miles per gallon), by class type*

	Mean	St. Dev.	Median	Range
Undergraduate N = 106	28.4	9.2	25	16-55
Graduate N = 130	27.8	6.9	28	15-55
Faculty N=67	27.6	6.6	25	17-48
Staff N=120	28.4	8.4	26	15-55

* Fuel efficiency observations limited by estimation method and respondent error

What is the relationship between fuel efficiency and commute distance?

Is it possible that individuals living further from campus are more sensitive to their fuel economy and more likely to drive high-efficiency vehicles? The correlation between fuel economy (miles per gallon) and road-networked commute distance (miles) is not very strong with a correlation coefficient equal to just .045.

Finding – The average campus fleet fuel economy is high relative to the current default in the Clean Air Cool Planet campus carbon calculator (equal to 22.1 mpg). Future GHG inventories might consider using survey-based estimated of fuel economy, which will better reflect campus mitigation policies (e.g., green parking incentives). However, additional data are needed to strengthen the fuel economy estimates, specifically for faculty. Also, there are no obvious determinants of fuel economy, including commute distance, as based on the 2010 survey data.

Among self-identified carpoolers, how many people ride per car?

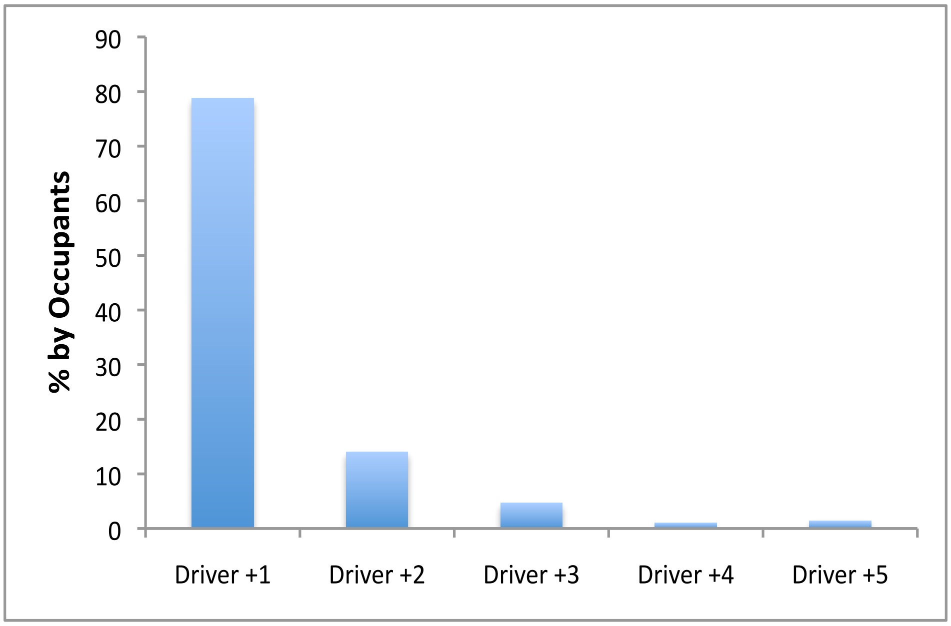

Figure 5 Distribution of occupancies for carpool trips among individuals who claim to carpool at least once per week

Finding – Among individuals that said they commute with at least one other person when they come to campus by car AND do so at least once per week, the average vehicle occupancy is 2.3 people, the median is 2 and the mode is 2. Almost 80 percent of carpool trips are made with just 2 people (the driver and a passenger) – less than 20 percent of carpool trips are made with 3 people.

Is there any difference in individual's willingness to carpool as a driver or passenger?

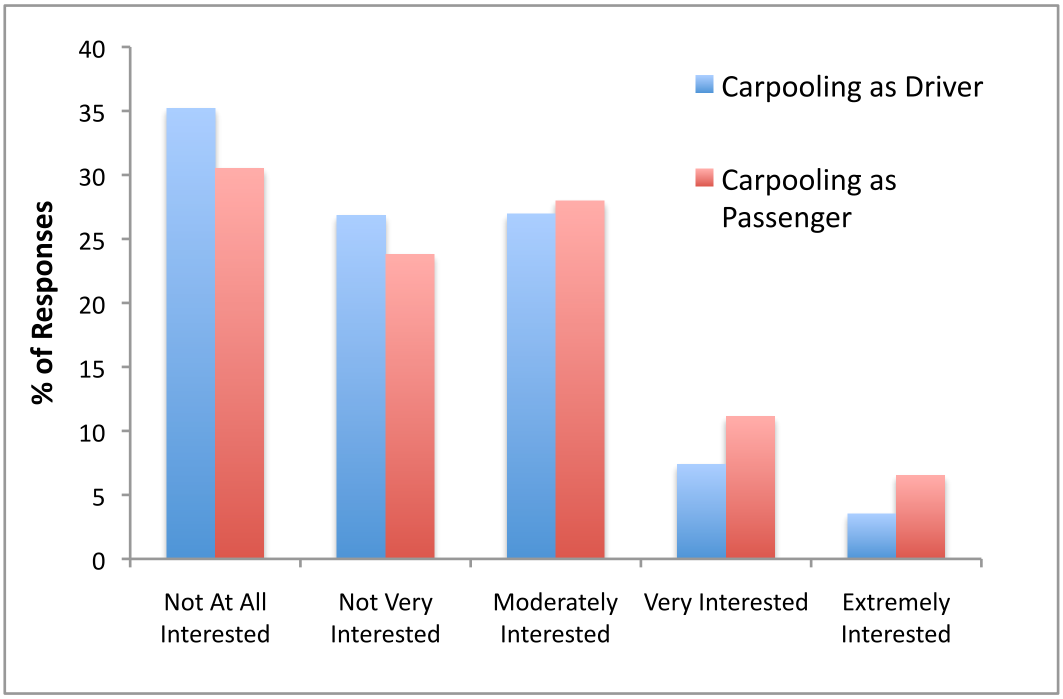

Figure 6 Interest in carpooling as either the driver or passenger

Are faculty and staff more interested in carpooling as drivers than students?

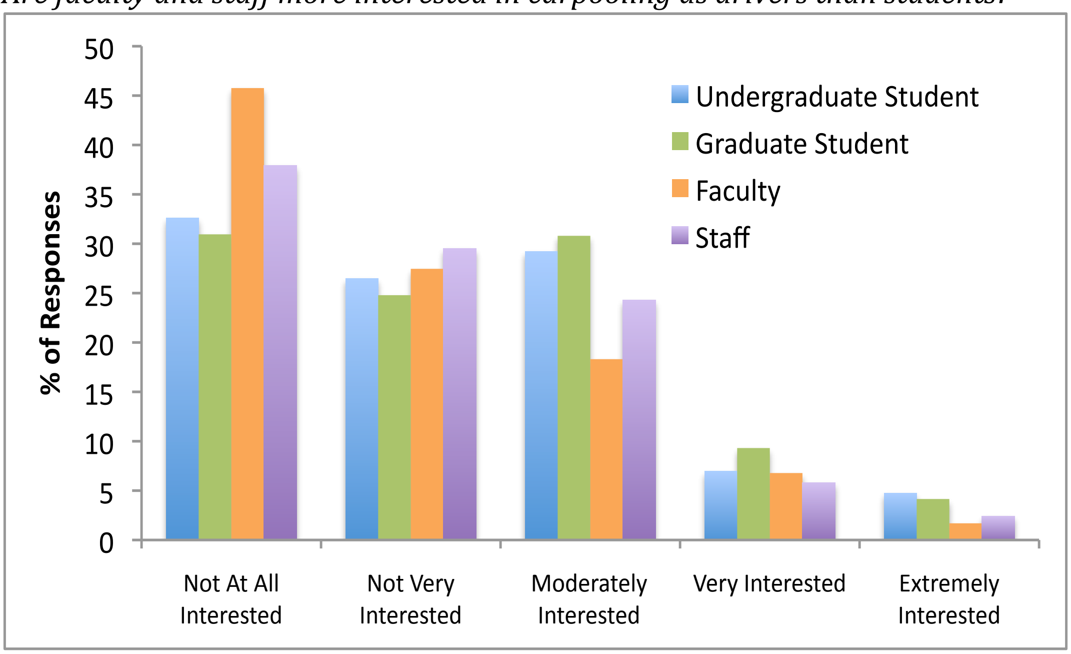

Figure 7 Interest in carpooling as DRIVER only, by class type

Are there any personal characteristics correlated with whether or not an individual would be interested in carpooling?

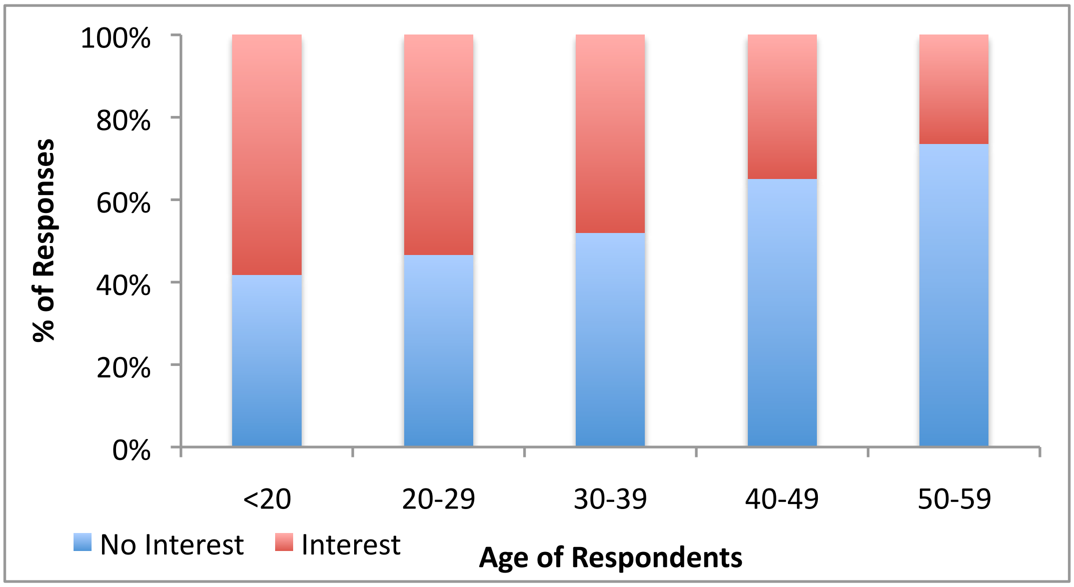

Figure 8 Interest in carpooling as PASSENGER only, by age of respondents

Finding – A small portion of the UM College Park population is interested in carpooling and people are generally more interested in carpooling as a passenger than as a driver. Who might the University target for carpooling programs? Commute distance, gender and status (e.g., student vs. employee) have a relatively small correlation with individual's interest in carpooling. Age, which is a likely proxy for income and individual's value of time and money, is strongly correlated with interest in carpooling.

Considering the cost of vehicle maintenance and fuel, how much would individuals be willing to pay per month to participate in a daily University vanpool?

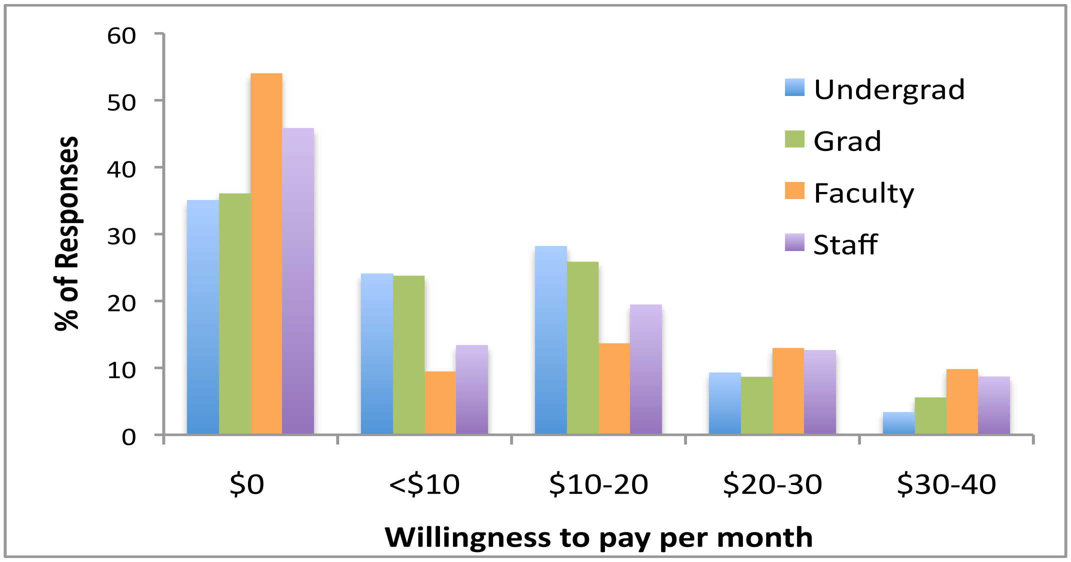

Figure 9 Willingness to pay for vanpooling ($/month), by class type

What factors would entice people to carpool more? What are the major barriers to carpooling?

Table 7 Top five incentives and barriers regarding carpooling/vanpooling

Rank	Incentives/Nudges to Carpool More	Factor difference over lower rank	Barriers Preventing Carpooling	Factor difference over lower rank
1	Frequent pick-up and drop-off times	2.2 *(e.g., frequent pick-up times are 2.2 times more important than convenient parking)*	Constrained schedule	1.1
2	More convenient parking	1.1	Dislike depending on others	1.1
3	Increasing gas prices	1.0	No time to wait for others	1.1
4	Guaranteed ride home	1.0	Personal car is needed for off-campus trips	1.0
5	Good company to ride with	Lowest	Concerned about becoming stranded on campus	Lowest

Finding – Individuals are willing to pay for a vanpooling service, especially students. Policies designed to promote carpooling/vanpooling should focus on the frequency of the service and be flexible per individual's constrained schedules.

What ZIP codes or surrounding cities expressed interest in carpooling and vanpooling and/or might be good candidates for a pilot vanpool program?

Table 8 ZIP codes and cities ranked by highest average interest in carpooling (as driver, then passenger) and corresponding willingness to pay for vanpool service

ZIP Code*	City	Average Interest as Driver	Average Interest as Passenger	Willingness to Pay for Vanpool*
21601	Easton	4.5	4.5	$30-40/month
21076	Hanover	3.5	2.5	$20-30/month
21211	Baltimore	3.3	3.3	$20-30/month
21409	Annapolis	3.3	3.3	$20-30/month
20601	Waldorf	3.0	4.3	$20-30/month
20470	Washington, DC	3.0	3.6	Under $10/month
20871	Clarksburg	3.0	3.0	$10-20/month
21030	Cockeysville	3.0	3.0	$10-20/month

** ZIP codes only included if 3 or more survey respondents reported residency in ZIP*

Finding – Consider targeting these ZIP codes for promotion of a vanpooling or carpooling program. DC residents are less willing to pay for a vanpooling program, which is likely due to access to more alternative transportation options.

Estimating GHGs emissions from survey data

Estimating GHG emissions from commuting is a trade off between efficient calculation and accuracy. While there are more accurate methods for estimating GHGs from commuting, using permit census data for example, it is possible to make an efficient and informed estimate of commuter GHGs with transportation survey data alone.[3] The steps below demonstrate how this can be accomplished while accounting for sample error inherent in survey data.

1) Using the population data and sample error estimates (Table 1), the mode choice distribution for single occupancy vehicle commuting (Table 3), average commute distance (Table 2), the median number of trips by class type (Table 5) and two additional assumptions[4], we can calculate the total average vehicle miles traveled in a year by the entire campus population.
2) Next, apply the error estimate corresponding with each class type and estimate a lower and upper bound for vehicle miles traveled (VMT).
3) Last, using vehicle fuel economy data (Table 6), we can calculate average total fuel consumption and $MTCO_2e$ emitted as well as upper and lower bounds. See Table 9 for methods and Table 10 for results.

Table 9 Factors included to estimate single occupancy commuters and VMT

Class.	Pop. Size (1)	Error (2)	SOV Mode Choice (3)	SOV Size (4)	Mean Dist. (5)	Median Freq (Trips/week) (6)	Roundtrip (7)	Weeks/year (8)
Undergrad	26,922	3.70%	32.00%	8615	13.44	6	2	32
Grad	10,719	3.40%	25.40%	2722	9.21	5	2	32
Faculty	2,273	5.10%	51.10%	1161	14.2	5	2	48
Staff	5,071	3.80%	65.30%	3311	15.62	5	2	48

* SOV commuters = (Column 1(C1)*(C3))=C4; VMT = C4*C5*C6*C7*C8; Bounds = multiply C3 & C5 by C2 and use new value to re-estimate C3 and C5 up & down; recalculate SOV commuters and VMT.

Table 10 Estimated vehicle miles traveled, gas consumed (gallons) and $MTCO_2e$

	Base (Avg.) Estimate	Lower Bound	Upper Bound
MTCO2e/year	26,922	24,251	29,594
Gallons/year	3,015,237	2,716,083	3,314,392
VMT/year	85,230,080	73,837,004	97,267,017

This approach represents a back of the envelope method for estimating GHGs from commuting and has a high degree of error. Also, because transportation surveys are time-intensive to plan and conduct, this is unlikely to be the most efficient method given GHG inventories should be performed with new data every year. However, the approach provides a valuable upper and lower bound, with a 95% confidence interval, against which to compare alternate GHG estimates.

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[3] A census covers an entire population whereas a survey samples a portion of the population.

[4] Assume students commute 32 weeks per year and faculty/staff 48 weeks per year; additionally, assume all trips are roundtrips.

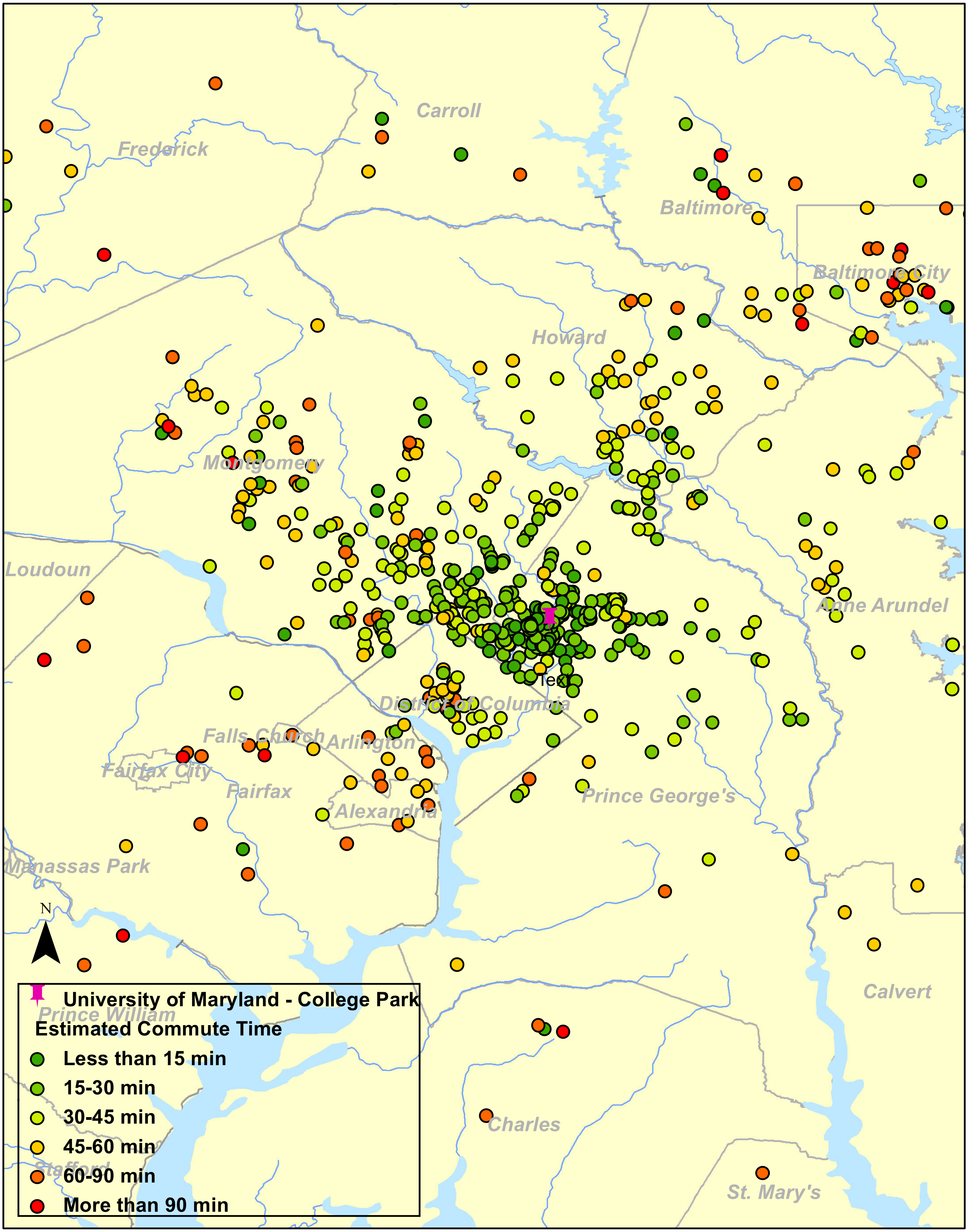
Mapping with Geographic Information System

There are multiple avenues for combining transportation survey data with GIS. The maps below display parking permit counts, distribution of commuter GHGs, and interest in carpooling by zip code. These maps are powerful tools for guiding policy development such as transportation service expansion.

The Maps Below include:

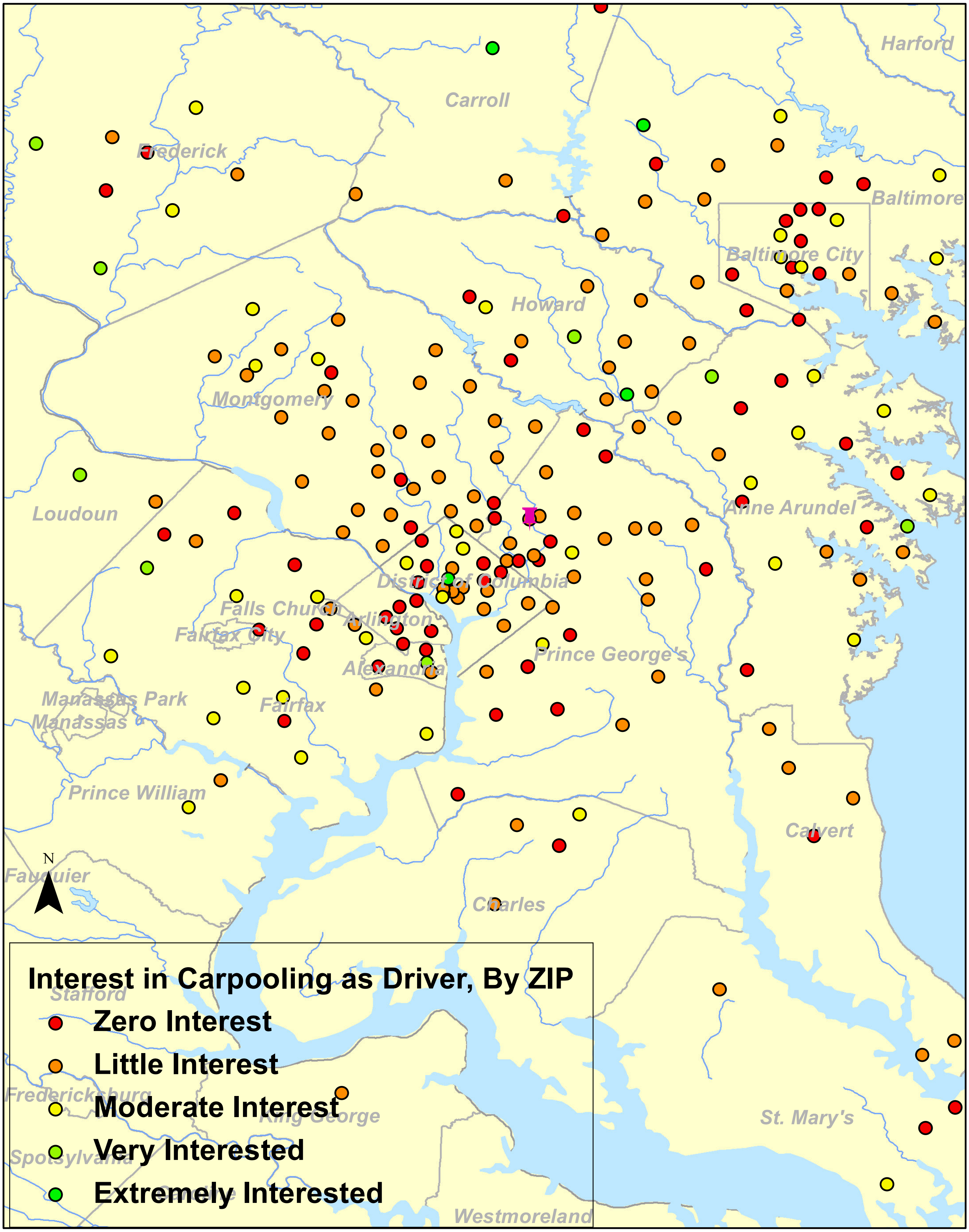
- Map 1: Estimated Commute Times, by Home Address
- Map 2: Commuter Interest in Carpooling as Driver, by ZIP
- Map 3: Permit Distribution, by Zip Code
- Map 4: Total Average GHG Impact per Week, by ZIP

Estimated Commute Times



Created by Center for Integrative Environmental Research
with 2010 UMD Campus Transportation Survey Data
 - Locations to the nearest City and Street.

Average Level of Interest in Carpooling as Driver, By ZIP Code



Created by Center for Integrative Environmental Research
with 2010 UMD Campus Transportation Survey Data
- Points reflect center of ZIP code

Permit Distribution by Zip Code

Legend

Permit Distribution

Number of Permits

- <5
- 5-10
- 11-25
- 26-50
- 51-100
- >100

Distance from Campus (mi.)

- 5
- 10
- 20
- 35

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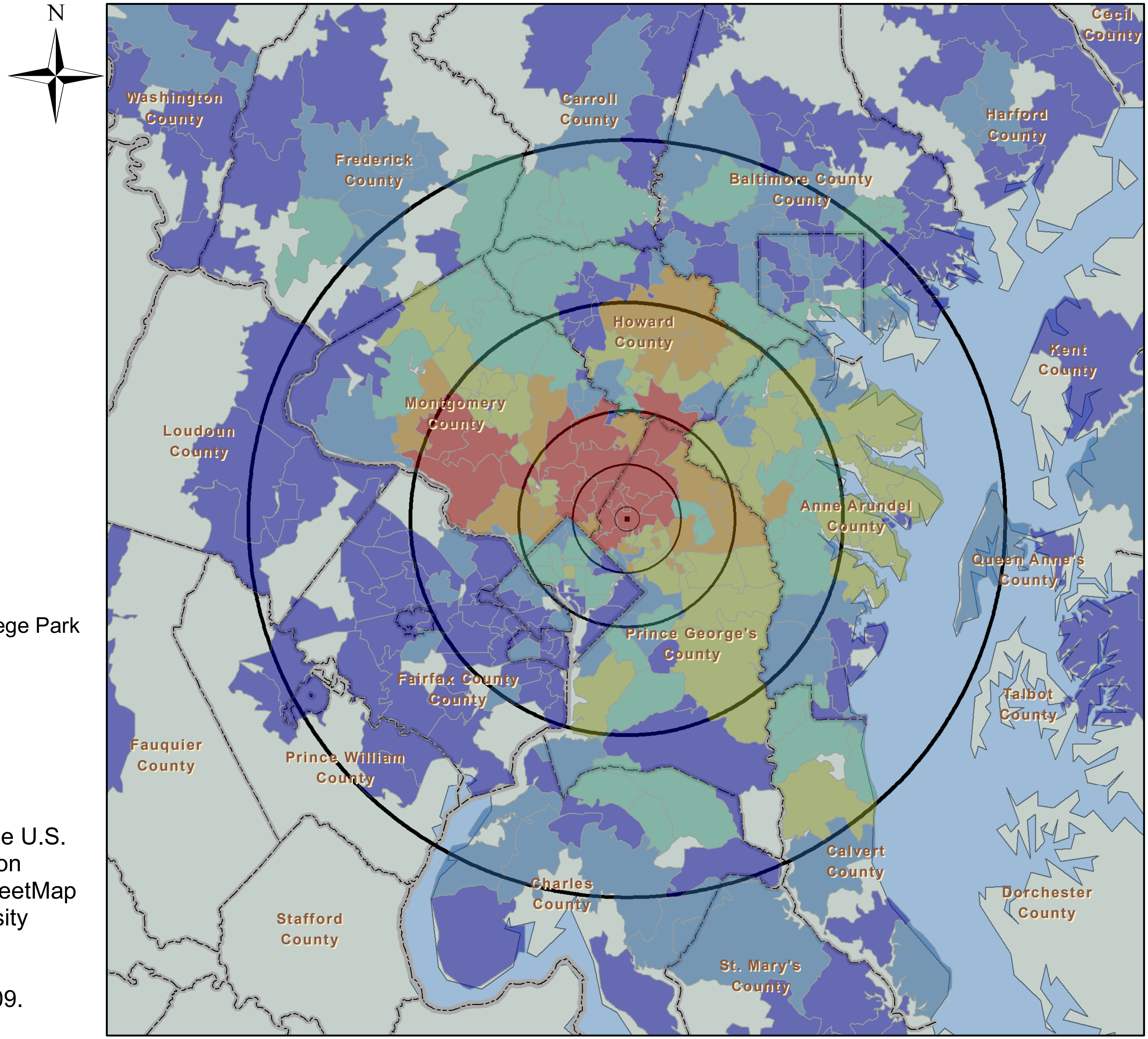

Zip code boundaries are from the U.S. Census 2000 Zip Code Tabulation Areas. Major Highways from SteetMap USA Permit data is from University of Maryland Deptartment of Transportation Online Permit Registration website for Fall 2009.

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Greenhouse Gas Impact per Week by Zip Code (kg-CO2)

Legend

kg CO2 Per Week

1 Std. Dev. = 1300kgCO2

- < -0.50 Std. Dev.
- -0.50 - 0.50 Std. Dev.
- 0.50 - 1.5 Std. Dev.
- 1.5 - 2.5 Std. Dev.
- > 2.5 Std. Dev.

Distance from Campus (mi.)

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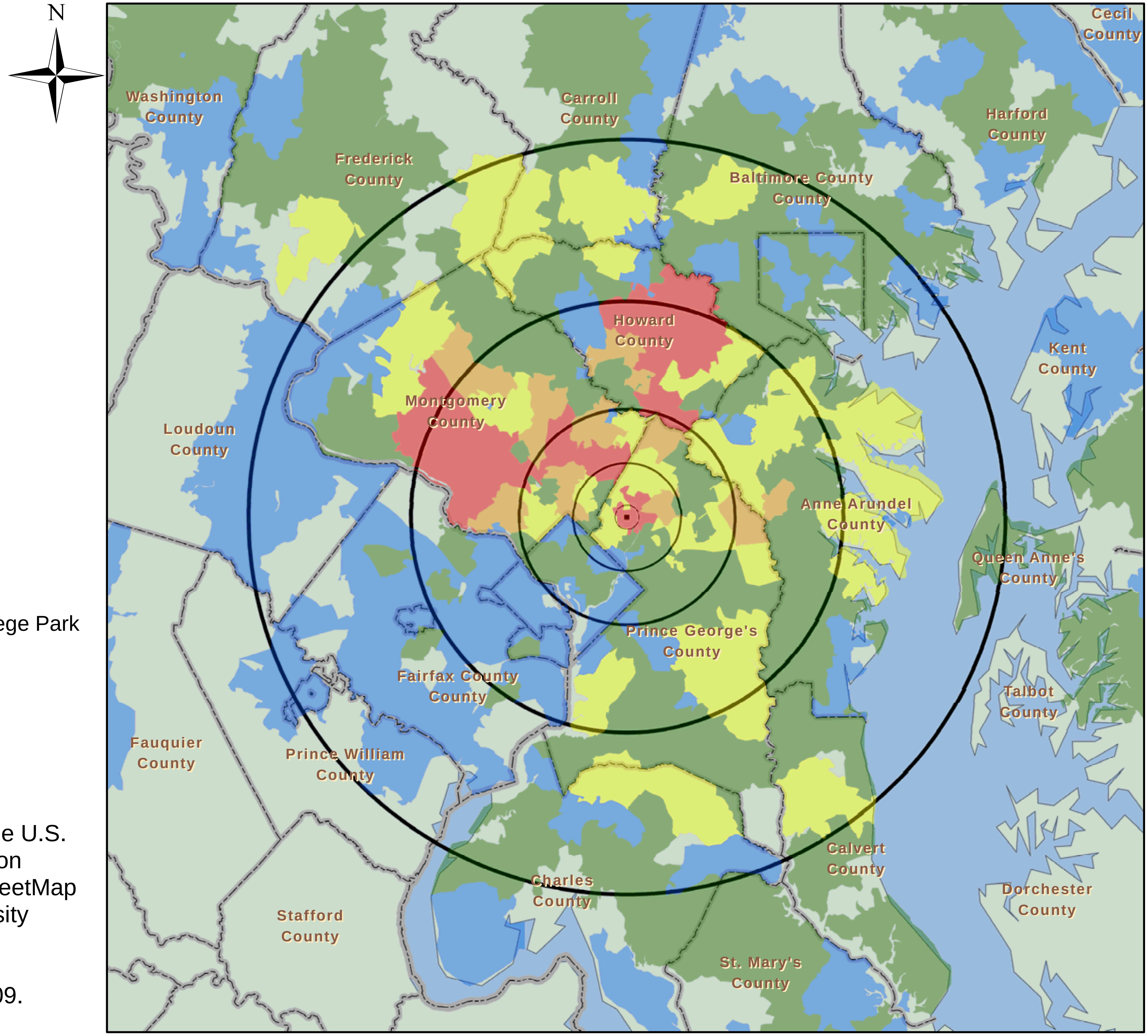

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Predictive Models

Transportation data allows analysts to develop mathematical models that can be used to establish relationships and ultimately predict the impact of policy. For example, what impact will a new "Park and Ride bus" have on commuter mode choice within a particular zip code? Using transportation survey data, it is possible to establish the relationship between "Park and Ride" usage and other variables such as individual's age, classification, distance from campus, etc., to predict how a new "Park and Ride" location might be received. With high quality survey data and policy questions to explore, campuses can save a lot of time through development and testing of these simple models.[5]

CIER has developed models using UM College Park survey data. At least one model relates how commute distance impacts behavior, including mode choice. The mode choice model suggests that a 1-mile increase in the distance of a commute will *increase* the odds of commuting by single occupancy vehicle by a factor of 1.038. For example, at a distance of 2.5 miles from campus, the probability that any given student commutes by single occupancy vehicle is 29 percent. At a distance of 28.5 miles from campus, the probability that any given student commutes by SOV is 51 percent.

Models typically demonstrate correlation, for example, between distance from campus and mode choice. However, causality, or the cause and effect relationship between two factors, is difficult to establish with models. Therefore, it is important for decision-makers to carefully apply the results of models in developing policies. Nonetheless, we can and should begin to apply models to assist with policy-making. Using the above model, for example, we anticipate that near-campus housing will lead to less single occupancy vehicle driving, and we can estimate the magnitude of that impact as it relates to the location and size of new housing.

Conclusion

The data applications and analysis presented in this document are not meant to be exhaustive. Instead this document should serve as an example of how valuable data can be in improving GHG inventories and formulating and evaluating mitigation policies. Data-driven decision-making, facilitated by good communication and presentation (e.g., data visualization), is critical to future sustainability and carbon management. It will be increasingly effective for colleges and universities to provide information feedback as a means for modifying commuter behavior. Whether through individually tailored phone applications or through community transportation surveys, the prospects for meeting sustainability goals will improve as universities find a way to advance understanding of commuting patterns.

[5] Note – Mathematical analysis is an area where faculty and students can be recruited to lend their expertise and help the campus meet its sustainability goals.

Additional Resources

1. Using data to understand behavior and drive modification:
    a. Goetz. T. *Harnessing the power of feedback loops*. Wired Magazine. June 2011. Available online at: http://www.wired.com/magazine/2011/06/ff_feedbackloop/all/1.
    b. Thaler, R. & Sunstein, C. 2008. *Nudge*. Yale University Press.
    c. McKenzie-Mohr, D & Smith, William. 1999*. Fostering Sustainable Behavior*. New Society Publishers.
    d. Community-Based Social Marking (CBSM.com). http://www.cbsm.com/public/world.lasso.

        Includes a free online version of the *Fostering Sustainable Behavior* book as well as articles and case studies of successful applications of community-based social marketing.