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Tools for Measuring Individuals' Climate Behaviors and Greenhouse Gas Impact

by K. Carrie Armel and Thomas N. Robinson

In the United States, the residential sector accounts for a significant proportion of the greenhouse gas (GHG) emissions produced each year. Sixty-two percent of vehicle emissions come from passenger cars and light-duty trucks, and one-quarter of non-transportation emissions come from residential sources.[1] Many individual-level behaviors that contribute to these emissions could be modified, for example, by purchasing compact fluorescent bulbs (purchasing behaviors), increasing one's refrigerator temperature (non-purchasing, one-time behaviors), regularly shutting off the lights (repeated behaviors or habits), or insulating one's hot water heater (complex behaviors that require expert assistance or are costly). Changes in such individual-level behaviors may play an important role in slowing climate change.

Reliable and valid tools for measuring the frequency, duration, or intensity of behaviors such as these, in conjunction with tools that provide accurate information about their GHG footprints, may help reduce emissions.[2] Such reductions could be achieved by using the data acquired with these tools in a variety of applications geared toward individuals, policymakers, program designers, and researchers. Some applications include the following:

> (1) This information can help generate goals and provide feedback to individuals in order to facilitate behavior change. Close to 40 studies have shown that providing individuals with feedback on their residential electricity use results in reductions of 5-15%, with the greater reductions occurring with more frequent or disaggregated feedback.[3] Research in public health has demonstrated that feedback is more effective at producing behavior change when used in conjunction with goals, and goals are most effective when they focus on proximate, specific behaviors.[4] The use of goals and feedback could be effective for reducing energy use by individuals, households, building managers, owners of commercial enterprises, and others.
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> (2) The data could help identify which behaviors and populations should be targeted with specific behavioral, technological, or policy interventions in order to develop more successful and cost-effective programs. For example, it seems prudent to direct resources toward interventions that target populations which frequently engage in large footprint behaviors. (Other factors, such as the potential malleability of the behaviors, acceptability of the interventions, and effects on equity should also be considered when selecting target behaviors and populations, but will not be discussed further here.)
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> (3) Data quantifying behavior prior to and following interventions allow for their assessment. Without the ability to reliably and validly estimate GHG-related behaviors with fairly high behavior-specific resolution, substantial effort, time, and resources may be wasted without knowing whether programs and policies are needed at all, or are beneficial, ineffective, or even harmful; which programs and policies should be replicated and disseminated; and which need to be ended, revised, or replaced. The effects of interventions are much more easily detectable when end use behaviors are disaggregated. This is because it is difficult to detect the effect of changes in a small subset of end use behaviors that an individual is likely to change at any given time, out of an aggregated household measure of electricity use.
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> (4) These data could enable a more diverse intervention kit for utilities. The ability to verify that a particular intervention resulted in energy savings allows utilities in some states to collect revenues for their energy efficiency efforts. Existing interventions are typically limited to rebates and cou-

K. Carrie Armel is a Research Associate at the Precourt Institute of Energy Efficiency at Stanford University. Thomas N. Robinson is the Irving Schulman, MD Endowed Professor in Child Health, Professor of Pediatrics and of Medicine, in the Division of General Pediatrics and the Stanford Prevention Research Center at Stanford University School of Medicine, and Director of the Center for Healthy Weight at Stanford University and Lucile Packard Children's Hospital at Stanford.

1. *See* U.S. Environmental Protection Agency (EPA), Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2006 (2008) (EPA 430-R-08-005); Michael P. Vandenbergh et al., *Individual Carbon Emissions: The Low-Hanging Fruit*, 55 UCLA L. Rev. (forthcoming 2008).
2. *See* Jamais Cascio, *The Cheeseburger Footprint*, Open the Future, July 7, 2008, http://openthefuture.com/cheeseburger_CF.html (last visited Oct. 8, 2008).
3. *See* Sarah Darby, The Effectiveness of Feedback on Energy Consumption: A Review for DEFRA of the Literature on Metering, Billing, and Direct Displays (Envtl. Change Inst., Oxford Univ. Press 2006).
4. *See, e.g.*, Dena M. Bravata et al., *Using Pedometers to Increase Physical Activity and Improve Health: A Systematic Review,* 298 J. Am. Med. Ass'n 2296 (2007).

pons because these are closely linked with energy savings behaviors, i.e., the purchase of an energy-efficient item. Higher resolution data make it easier to verify that other types of programs such as media messages or in-home feedback displays result in energy savings. This is because the relevant data are not obscured through aggregation, as described above, and also because a clear link can be established between the behaviors targeted by the intervention and those behaviors that individuals actually change.

(5) These data could improve the effectiveness of research directed at reducing energy use. Behavior change techniques are most effectively evaluated using end use specific data, for the reasons described above. Building research could also benefit, for example, actual building energy use, which is much higher than that predicted by models, but few data are currently available to identify the origins of this discrepancy. A more detailed understanding of the frequency and timing of various end use behaviors could shed light on the problem. Specific data might also enable engineers to determine which appliances or appliance subcomponents should be targeted for energy efficiency improvements.

(6) Data on end use behaviors could be used to estimate individual and population frequencies of GHG emissions-related behaviors and changes in their frequencies over time, for example, to improve models of energy use and to aid policymakers in understanding energy consumption trends.

(7) The data could foster innovation that enables individuals to reduce their energy use even further. Information regarding individuals' energy use could be incorporated into online social networks or video games to increase motivation to reduce energy consumption. For example, data regarding the actual energy consumption of one's individual appliances could be compared to the expected energy consumption of those appliances contained in databases[5] in order to alert users when an appliance should be repaired or replaced. When coupled with control devices, information regarding the energy use of appliances or temperature systems could enable individuals to adjust use of these items remotely or automatically with presets. A better understanding of where energy is used and under what conditions could enable laypeople to develop innovative solutions to reducing energy use.

This Article surveys the range of tools that are currently available for measuring the carbon footprint of individual behaviors and the frequency, duration, and intensity of those behaviors. Different types of tools might be suitable for the different applications described above; in this Article we review tools that include text-based documents, footprint calculators, surveys and logs, and measurement technologies. We also discuss the characteristics of the tools. For example, we review which categories of behaviors are covered by the tool, e.g., home electricity, gas, transportation, food; the tool's ability to evaluate the frequency of behaviors with specificity and sensitivity; whether carbon footprint estimates are provided by the source; and whether the source is easy to use.

I. Tools

A. Text-Based Documents

Several peer-reviewed text-based documents are available that estimate the carbon footprint of behaviors. These generally derive estimates from large government or industry data sets and make additional assumptions and calculations to measure the impact of specific behaviors or categories of behaviors. These documents focus on electricity and transportation,[6] food,[7] or a broad variety of categories of behaviors.[8] However, many of these sources cover only a small subset of behaviors or provide statistics that are difficult to use for the aforementioned applications. There are also several government and academic documents that focus on the carbon impact resulting from the production of food and goods.[9] However, these dense documents generally require additional calculations and assumptions to produce figures for the uses described above, they tend to be based on European goods, and it is questionable whether the figures generalize to the United States. In summary, these documents likely provide the best data available to date on the carbon footprint of individual behaviors, although they could be made more specific and/or user-friendly, and there are significant gaps in knowledge for behaviors related to food and product consumption.

B. Online Calculators

Recently online carbon footprint calculators have become popular. Most of these include only very general questions, such as overall home electricity use and miles driven.[10] This makes the calculators unsuitable for the purposes described above. Also, there are large inconsistencies between online

5. *See, e.g.*, excel files on each Energy Star® product page, http://www.energystar.gov/index.cfm?fuseaction=find_a_product. (*Editors' Note: A period is necessary at the end of this URL.*) *See also* U.S. Dep't of Energy, *Energy Star Qualified Products*, http://www.energystar.gov/ia/products/prod_lists/tv_vcr_prod_list.xls (last visited Sept. 15, 2008).

6. *See* Vandenbergh, *supra* note 1; Richard Conniff, *Counting Carbons*, 26 DISCOVER 54 (2005); Paul C. Stern & Gerald T. Gardner, *The Short List: The Most Effective Actions U.S. Households Can Take to Curb Climate Change*, ENV'T MAG. (forthcoming).

7. *See* Gidon Eshel & Pamela A. Martin, *Diet, Energy, and Global Warming*, 10 EARTH INTERACTIONS 1-17 (2006).

8. *See* Bin Shui & Hadi Dowlatabadi, *Consumer Lifestyle Approach to U.S. Energy Use and the Related CO_2 Emissions*, 33 ENERGY POL'Y 197 (2005); Chris Goodall, *How to Live a Low-Carbon Life: The Individual's Guide to Stopping Climate Change* (Earthscan Publications 2007).

9. *See, e.g.*, Tomas Ekvall et al., *Life Cycle Assessment of Packaging Systems for Beer and Soft Drinks: Main Report* 1-388 (Danish EPA, Envtl. Project, Report No. 399, 1998); Marko P. Hekkert et al., *Reduction of CO_2 Emissions by Improved Management of Material and Product Use: The Case of Primary Packaging*, 29 RESOURCES, CONSERVATION & RECYCLING 33 (2000); Chris Foster et al., *Environmental Impacts of Food Production and Consumption: A Report to the Department for the Environment, Food, and Rural Affairs* (Manchester Business School for DEFRA, London 2006).

10. *See* Evan Mills, *The Home Energy Saver Library: Carbon Footprint Calculators*, http://hes.lbl.gov/hes/carbon-calculators.html (last visited Sept. 15, 2008).

carbon calculators,[11] and their reliability and validity are unknown. Here we describe just two of the numerous calculators. These assess specific behaviors and take a rigorous approach to acquiring their figures.

The Home Energy Saver (HES)[12] is extremely specific and comprehensive regarding home energy use; questions investigate home construction characteristics, types of appliances and heating and air conditioning systems, and frequency of use of this equipment. The authors of the calculator plan to develop a behavior module in which an individual can choose to answer only those questions that relate to day-to-day behaviors rather than home construction and appliance purchase information.[13] The HES is an excellent tool for surveying a comprehensive set of specific home energy characteristics and end uses, and it provides a sufficient range of response options on each question to detect differences in energy use on these across individuals or within an individual across time. The tool is also very accurate in that it closely predicts actual financial expenditures based on the non-financial user input described above. However, using the tool requires significant time to gather and input data. Also, information on energy use or GHG emissions for individual end uses must be derived from supplementary documentation that the group provides[14]—automated results are reported in terms of one's estimated financial costs by end use category as well as aggregate potential annual financial, energy, and carbon emission savings.

The Berkeley Institute for the Environment[15] calculator has a broader focus in that it covers home energy use as well as behaviors relating to transportation, food, and the purchase of goods and services. However, it clusters behaviors in a way that is much less specific than the HES. carbon dioxide figures are derived from national databases. For example, for food and services, a life-cycle assessment model is used to convert monetary expenditures in a particular sector of the U.S economy, e.g., meat, vegetables, all services, to the corresponding GHG emissions produced from this expenditure (based on the total GHG emissions for that sector). However, because behaviors are measured in terms of money spent by an individual on a category of behavior, rather than on the frequency of individual behaviors, interpretation is confusing for many of the applications described at the beginning of this Article.

C. Surveys and Logs

In the past few decades, many surveys have been developed to measure pro-environmental behaviors. These typically ask about a relatively small number of environment-related behaviors and have been used to investigate whether they are correlated with attitudes or other psychological constructs. Many cover sustainability in general, and include questions that are not specific to climate change, such as household chemical use, battery recycling, etc.[16] Of the surveys that deal with climate-relevant behaviors, some deal only with recycling[17] or transportation,[18] or estimate behaviors indirectly, e.g., appliance ownership,[19] and others code behaviors on a binary scale, which diminishes their sensitivity for detecting variations and changes in behavior, particularly in individuals.[20] The majority of these measures do not meet the needs laid out at the beginning of this Article because they do not cover a sufficient number of individual behaviors relevant to climate change.

The Stanford Climate Change Behavior Survey is a recently developed self-administered survey designed to assess the frequency, duration, or intensity of climate change-relevant behaviors performed by individuals.[21] The instrument covers several categories of behavior (electricity and gas use, transportation, food, and waste) and inquires about many specific behaviors within each of these categories. Another benefit is that the response options for each question were designed to be sufficiently sensitive to detect behavior change over time or across individuals. However, the survey is geared only toward individuals, such as renters or high school and college students. A more comprehensive version could target homeowners, e.g., currently there are no questions on appliance purchases or retrofits. Also, there is presently no conversion for the behaviors to their carbon footprint.

StepGreen is an online tool that allows individuals to log over time whether or not they perform specific behaviors,

11. *See* J. Paul Padgett et al., *A Comparison of Carbon Calculators*, 28 Envtl. Impact Assessment Rev. 106 (2008).

12. *See* Evan Mills, *Home Energy Saver: The First Web-Based Do-It-Yourself Audit Tool*, http://hes.lbl.gov (last visited May 10, 2008).

13. E-mail from Evan Mills, Founder, Home Energy Saver Development Team, to author (Mar. 9, 2008) (on file with author).

14. *See* Evan Mills, *The Home Energy Saver: Documentation of Calculation Methodology, Input Data, and Infrastructure* (Ernest Orlando Lawrence Berkeley National Laboratory, Report No. LBNL-51938, 2007).

15. *See* Christopher M. Jones, *CoolClimate Carbon Footprint Calculator*, http://bie.berkeley.edu/calculator (last visited Sept. 15, 2008).

16. *See* Florian G. Kaiser, *A General Measure of Ecological Behavior*, 28 J. Applied Soc. Psychol. 395 (1998); Orjan Wiidegren, *The New Environmental Paradigm and Personal Norms*, 30 Env't & Behav. 75 (1998); Donald E. Blake et al., *Canadian Public Opinion and Environmental Action: Evidence From British Columbia*, 30 Canadian J. Pol. Sci. 451 (1997).

17. *See* Stewart Barr, *Factors Influencing Environmental Attitudes and Behaviors: A U.K. Case Study of Household Waste Management*, 39 Env't & Behav. 435 (2007); Gregory A. Guagnano et al., *Influences on Attitude Behaviour Relationships, a Natural Experiment With Curbside Recycling*, 27 Env't & Behav. 699 (1995); Brian E. Porter et al., *Solid Waste Recovery: A Review of Behavioral Programmes to Increase Recycling Behaviour*, 27 Env't & Behav. 122 (1995); P. Wesley Schultz & Stuart Oskamp, *Effort as a Moderator of the Attitude-Behaviour Relationship: General Environmental Concern and Recycling*, 59 Soc. Psychol. Q. 375 (1996).

18. *See* Linda Steg & Charles Vlek, *The Role of Problem Awareness in Willingness-to-Change Car Use and in Evaluating Relevant Policy Measures*, *in* Traffic and Transport Psychology: Theory and Application 465-75 (Talib Rothengatter & Enrique Carbonell Vaya eds., 1997).; Sonja Haustein & Marcel Hunecke, *Reduced Use of Environmentally Friendly Modes of Tansportation Caused by Perceived Mobility Necessities: An Extension of the Theory of Planned Behavior*, 37 J. Applied Soc. Psychol. 1856 (2007).

19. *See* Brigitta Gatersleben et al., *Measurement and Determinants of Environmentally Significant Consumer Behavior*, 34 Env't & Behav. 335 (2002).

20. *See* Ida E. Berger, *The Demographics of Recycling and the Structure of Environmental Behavior*, 29 Env't & Behav. 515 (1997); John Painter et al., *Is There a Generalized Energy Conservation Ethic? A Comparison of the Determinants of Gasoline and Home Heating Energy Conservation*, 3 J. Econ. Psychol. 317 (1983).

21. *See* K. Carrie Armel et al., *Validation of the Stanford Climate Change Behavior (SCCB) Survey: Assessing Greenhouse Gas Emissions-Related Behaviors in Individuals and Populations*, Climatic Change (forthcoming).

and it covers a large diversity of behaviors in several categories.[22] It also provides average GHG estimates of the footprint of each of those behaviors and makes use of social networking, norms, visualization, and suggestions about specific actionable items. However, the tool only allows individuals to indicate whether they are doing a behavior or not, so it has low sensitivity to changes in behavior over time or between populations for any given behavior. The GHG footprint for each behavior assumes average frequency, duration, or intensity of the behavior, and the tool is not transparent about where these figures come from.

D. Measurement Technologies

Another approach to assessing behaviors related to GHG emissions is to quantify the actual impact of individuals' or households' electricity or gas usage using, for example, electricity meters.[23] To date, these devices have measured overall consumption; technology that disaggregates consumption by end use behaviors has been too labor- or cost-intensive to be feasible for most applications, including sufficiently powered population-based studies.

However, technologies are rapidly emerging that may allow for improved energy measurement at lower cost and with easier installation. So called smart meters—electronic meters that replace the old mechanical ones and are capable of transmitting overall home electricity use wirelessly, along power lines, or through high bandwidth digital communications in almost real time to outside sources, e.g., the utilities, or within the home to Home Area Networks (HANs)—are being deployed throughout Europe and the United States. For example, by 2012, all California residential and commercial buildings are expected to have smart meters. Dozens of third-party vendors are developing tools to display or augment the smart meter data. For example, some companies are developing web interfaces that analyze and display data from smart meters, e.g., GreenBox. Others are developing wireless HANs that sense electricity use on individual appliances, e.g., Tendril, Widefield Technologies, or disambiguation algorithms that derive appliance-specific data from overall home electricity use, e.g., Electric Power Research Institute; Shwetak Patel, University of Washington; Dane Kouttron, Rensselaer Polytechnic Institute. Still others are embedding chips in appliances to allow individuals to control them, e.g., Echelon, General Electric, Whirlpool. In September 2008, a workshop was held by Stanford's Precourt Institute of Energy Efficiency on this topic, and workshop materials are available online.[24]

Similar technologies are under development for transportation behaviors. For example, Enviance, EnCana Corporation, and Cartasite Incorporated have partnered to measure, record, and provide feedback on the acceleration rates and fuel use of 400 participants in a Denver-based study.[25] The UbiGreen project, a collaboration between Intel, the University of Washington, and Carnegie Mellon University, uses mobile phones, sensors, and machine-learning techniques to automatically recognize transportation behaviors such as walking, biking, and moving in a motor vehicle, and records and provides feedback on this data.[26]

These technologies offer great potential to objectively measure electricity, natural gas, and gasoline consumption. These measurements can then fairly easily be converted into GHG emissions. The technologies also promise the opportunity to measure end use behaviors with a fairly high degree of specificity. Thus, they would acquire the two types of data described at the beginning of this document: (1) the carbon footprint of behaviors; and (2) the frequency, duration, or intensity of the behaviors. Furthermore, correspondence between survey questions and emissions could be established by collecting self-report survey data on individuals during the same period that their appliance-specific electricity use is measured. This would be useful for acquiring impact estimates of specific behaviors so that when objective measures of emissions are not feasible, surveys could be used to assess impact. Establishing a relationship between behaviors and objective measures of GHG emissions could also improve the resolution and accuracy of carbon calculators.

II. Conclusion

Data regarding the frequency, duration, or intensity of specific end use energy behaviors, as well as the carbon footprint of these behaviors, could help reduce GHG emissions through a variety of applications. Delaying action until ideal tools are developed or better data are available is obviously not an option, but many useful tools are available now, and emerging technologies offer great promise in the near future. These tools tend to focus on electricity, natural gas, and transportation behaviors, while individual data on food and purchasing behaviors is mostly lacking. This is in part due to the difficulty in computing figures for food and purchasing behaviors, e.g., the source of raw materials can vary significantly over time and geographic region, although grocery store databases derived from "club card" use, GHG registries, carbon emissions trading programs, and improved labeling, may eventually produce useful data on these behaviors as well.

Note: Many of the documents or tools discussed in this Article, as well as related ones, are conveniently linked through the Precourt Institute for Energy Efficiency website.[27]

22. *See* Jennifer Mankoff et al., *StepGreen*, http://stepgreen.org/ (last visited Sept. 15, 2008).

23. *See* Richard D. Katzev & Theodore R. Johnson, *Comparing the Effects of Monetary Incentives and Foot-in-the-Door Strategies in Promoting Residential Electricity Conservation*, 14 J. Applied Soc. Psychol. 12 (1984); Richard A. Winett et al., *Effects of Television Modeling on Residential Energy Conservation*, 18 J. Applied Behav. Analysis 33 (1985). For a review, see Darby, *supra* note 3.

24. *See* K. Carrie Armel, *Energy and Feedback Workshop*, http://piee.Stanford.edu/cgi-bin/htm/Behavior/2008_energy_and_feedback_workshop.php (last visited Sept. 15, 2008).

25. *See* Deedee Correll, *Keeping a Green Eye on Drivers,* L.A. Times, Apr. 6, 2008, *available at* http://articles.latimes.com/2008/apr/06/nation/na-greendriving6 (last visited Sept. 15, 2008).

26. *See* Jon Froehlich et al., *UbiGreen: Using Mobile Phones as a Persuasive Technology to Affect Daily Transportation Practices*, 2008 Behavior, Energy, and Climate Change Conference, Sacramento, CA (abstract accepted).

27. *See* K. Carrie Armel, *Behavior and Energy Tools*, Stanford's Precourt Institute of Energy Efficiency, 2008, http://piee.stanford.edu/cgi-bin/htm/Behavior/tools.php?ref=nav4 (last visited Sept. 15, 2008).