Residential Windows, Greenhouse Gas Emissions and the Potential of Emerging Window Technologies

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ABSTRACT

Windows are typically considered to be some of the least energy – efficient components in the residential building envelope in the US, yet few studies have characterized their aggregate energy and environmental impacts. This study combines a national survey of residential energy end uses with computer simulations of window energy performance to estimate the primary energy consumption and carbon emissions associated with residential windows. We consider potential energy savings from the complete replacement of the US window stock with both present and future high-performance fenestration technologies. We find that tomorrow's high performance windows have the potential for dramatic reductions in the energy consumption and carbon emissions associated with the US residential window stock, and a 10% reduction in emissions and consumption associated with residential heating and cooling.

INTRODUCTION

Recent scientific evidence suggests that global climate change is of significant concern to humanity. It is widely accepted in the scientific community that elevated concentrations of "Greenhouse Gases" such as carbon dioxide) are responsible for much of observed and predicted global warming *[1]*. Since the majority of anthropogenic greenhouse gas emissions are the result of fossil fuel combustion, a reduction in non-renewable energy consumption will be an important part of any effective strategy to mitigate global climate change. By performing conventional tasks with a smaller energy input, energy-efficient technologies represent one of the easiest strategies to achieve lower energy consumption, and thus lower greenhouse gas emissions.

In the US, windows are one of the least energy-efficient components of homes. In the winter, they conduct heat to the outdoors, while in the summer, solar gains require the usage of additional air conditioning. As a result of these inefficiencies, windows are responsible for roughly a third of space conditioning energy consumption in US homes [2]. Few studies have directly addressed the effects of residential windows on national energy consumption. A 1996 study estimates residential windows are responsible for 1.7 Quadrillion BTU (Quads) of primary energy consumption annually [3], while a back-of-the envelope calculation based on computer simulations places this value at 2.8 Quads for 2002[1]. These values indicate that residential windows in the US are responsible for 2-3% of US energy consumption. Furthermore, although no previous study has addressed the climate change impacts of window energy consumption in detail, a simple calculation suggests that residential windows in the US are responsible for 0.4 - 0.7% of global anthropogenic CO_2 emissions [4].

Improving the energy efficiency of residential windows may offer great potential for reducing the carbon emissions of US residences. A 1996 study suggested that the then-top of the line window technology, known as "Low-e", could reduce window-related energy consumption by over 40% if it were installed in all US homes [3]. Low-e is now a well-accepted product, and future windows will be even more efficient than low-e, let alone those found in the majority of the US housing stock today. Computer simulations

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[1] See Appendix A for an overview of this back-of-the-envelope calculation.

suggest that emerging technologies could turn windows into an energy asset by harvesting "free" solar heat. In many homes, this could reduce energy demand for annual space conditioning by 20 – 30% even in comparison to today's high-performance technologies [5].

Although emerging window technologies appear to be a promising tool in reducing residential energy consumption in the US, potential savings in greenhouse gas emissions have not been characterized. A significant obstacle to describing these savings is a poor understanding of the current emissions attributable to residential windows. Since the existing window stock and the carbon-intensiveness of energy consumption vary widely across the US, potential reductions in greenhouse gas emissions may differ from already-projected energy savings at the household level, as discussed above. By combining computer energy simulations with regional housing data, this paper will characterize both the current carbon emissions attributable to windows, and estimate the potential for future emissions savings through the use of emerging window technologies.

Fenestration Technology: A Background

Window performance is generally determined by three physical phenomena:

- **Heat Loss**. Since windows are almost always less insulated than the walls around them, heat transfer through windows represents significant energy inefficiency in the wintertime. A metric known as the *U-factor* describes the thermal permeability of a window – the lower the U factor, the better insulated a window is.
- **Solar Heat Gain**. Glass is more transparent to visible light than infrared radiation (heat). This means that sunlight will warm a room as floors, walls and furniture absorb it and convert it to heat. In the winter, this is a very effective means of providing free heat. However, in the summer, large solar heat gains translate into excessive need for air conditioning. The *Solar Heat Gain Coefficient (SHGC)* is a metric used to describe this property. A SHGC of 1.0 means that all solar radiation incident on a window will be transmitted through it, whereas a SHGC of 0 means that no radiation is transmitted.
- **Infiltration** – Aging and poor installation may prevent windows from effectively sealing the building envelope. As a result, unconditioned air can leak or *infiltrate* through cracks. This short-circuits a building's space conditioning system and reduces energy efficiency.

A variety of technologies have been developed to reduce energy inefficiencies resulting from the above phenomena. Double and triple glazed windows are some of the simplest solutions, and result in a considerable reduction in heat loss. The use of *low-e*, a special coating applied to multiple-glazed windows, significantly reduces radiative heat transfer. Over 40% of windows sold today take advantage of this technology [6]. Some low-e windows, especially those sold in the southern US, employ *spectrally selective* coatings that block invisible solar radiation, allowing for very low SHGCs. Today's very best windows use several of these technologies in tandem to achieve very low U factors and locally appropriate levels of solar heat gain. Simulations suggest that use of these windows in a typical, recently-constructed home results in annual space heating energy consumption around 10% lower than homes equipped with more conventional low-e windows [5].

The optimization of solar gain has remained a persistent challenge in window design. Spectrally selective windows are clearly the appropriate choice for southern US climates, where cooling dominates space conditioning energy consumption. Likewise, high-solar gain windows are desirable in northern climates, where heating demand is high and cooling is less of an issue. Unfortunately, the majority of US climates require significant amounts of both forms of space conditioning over the course of a year. Both low- and high- solar gain windows thus require sacrificing optimal energy performance for part of the year. A potential solution to this limitation is a "dynamic" window with solar gain properties that could be altered to match seasonal needs. In the winter, solar gains would be intelligently utilized to reduce heating energy consumption, while in the summer low solar gain would minimize cooling costs. Computer simulations suggest that dynamic windows could turn windows from energy liabilities into energy assets – a home with dynamic windows would consume less energy than a home with no windows at all. This would result in annual space heating energy consumption 20-30% lower than homes equipped with low-e windows [5]. A variety of technologies currently under development could make dynamic windows feasible in the relatively near future.

Today, dynamic windows belong to the realm of the conceptual, but it would be expected that these windows would result in the greatest savings in energy consumption in climates that have both significant heating and cooling seasons. While this describes many US climates, much of the southern US has relatively small heating demand. To a lesser extent, some northern climates have very small annual air conditioning needs. In these climates, a future generation of climate-specific windows that builds on today's high-performance technologies could conceivably result in deeper energy savings. Windows for the northern market would have better insulating properties without sacrificing solar heat gain, while windows for the southern market would focus on controlling solar heat gain without compromising transmittance of visible light.
Apte, Arasteh and Huang term these technologies "ultra" windows and found that these windows could result in greater annual energy savings than dynamic windows in many southern climates [5]. In some northern climates, greater annual energy savings were seen with ultra windows as well, but this came at the cost of much greater peak electricity consumption during the summer.

Apte, Arasteh and Huang demonstrate that emerging fenestration technologies have the potential for large energy savings in newly-constructed homes. However, window performance has improved dramatically over the past thirty years. This suggests that the replacement of older windows in already-existing homes may offer even larger energy savings. We recognize that the development of both emerging fenestration technologies – dynamic windows and ultra windows – presents significant technical challenges. This study seeks to inform future research and development efforts by comparing the potential benefits of these two technologies when applied to the existing building stock.

METHODS

This section provides an overview of the model used to estimate window-related carbon emissions for US homes. The methods build on the bottom-up approach used by Frost (1996) [3] to estimate national window energy use, but have been modified to gain greater insight into the uncertainty of predictions, provide greater regional disaggregation and to look specifically at carbon emissions.

We started with Residential Energy Consumption Survey (RECS) data that provide information on building and equipment characteristics, window choice, and annual space conditioning energy consumption at the household level. Next, we used computer energy simulations with region-specific "prototype homes" to determine the fraction of RECS-reported heating and cooling consumption that is attributable to windows. We then used a spreadsheet-based Monte Carlo model to map the predicted energy use of windows to the national survey of homes and account for uncertainties involved in these assignments. Within the spreadsheet model, we established a set of scenarios to allow us to estimate potential energy savings from future window technologies. Finally, region- and fuel-specific emissions factors were introduced to convert site energy consumption into the national carbon emissions attributable to residential windows.

Home Energy Consumption: the RECS Survey

The principal dataset used in this study comes from the Residential Energy Consumption Survey (RECS) [7]. This survey is conducted on a statistically representative probability sample of U.S. homes every three to four years by the Energy Information Administration (EIA), and reports a wide range of energy-related information for roughly 8,000 US residences. In this study, we chose to work with the 1993 edition of the RECS. Although it has been superceded by two more recent surveys, this edition provides information about window choice that is unique. Our study is thus limited to analyzing window energy consumption in 1993.

We considered only detached single-family homes for two reasons: first, single family homes comprise a majority of the US housing stock [7] and new construction [8], and thus play the most significant role in new window purchases; second, detached single-family homes are more easily modeled than other types. In 1993 single-family homes represented 62% of the US housing stock, and were responsible for 74% of residential sector end-use energy consumption [9].

Using the Microdata format of RECS, which reports individual responses for each of the 4,350 detached single family homes in the study population, we were able to examine correlations among household characteristics. For example, a homeowner who purchases highly efficient windows may be more likely to invest in a new, more efficient furnace as well, and only household-level data would be able to effectively capture the implications of this correlation.

We limited our study to RECS survey questions most relevant to the effects of climate and location, home construction, window choice, and space conditioning equipment on greenhouse gas emissions (Table 1). Additionally, the RECS survey reports the 1993 household energy consumption for each fuel, as reported by the local utility. We used the energy consumption of the four main residential heating fuels in the US (Electricity, Natural Gas, Liquefied Petroleum Gas (LPG) and Fuel Oil) which were used by 94% of the homes in the US. RECS uses a statistical model to apportion this energy consumption to different end uses, such as cooking, lighting, and most importantly for this analysis, space heating and air conditioning. Using long-term regional heating and cooling degree-day data [10], we applied a correction factor to remove any effects of short-term weather variation in the usage data for 1993[2].

Estimating the Energy Requirements of Windows

We estimated the energy consumption of windows in two steps. First, we developed a database of the energy performance characteristics (U factor and Solar Heat Gain Coefficient) of common US window types. Second, we simulated the energy performance of each window type in region-specific "prototype homes", that is, homes that represent typical regional construction patterns. This allowed us to determine the percentage of total heating and cooling energy consumption attributable to windows for each combination of prototype home and window type.

We created a database of 26 window types to represent both current and future window stock. The database is split into two segments – contemporary and future window technologies (Table 2). We considered contemporary windows with three different frame types (aluminum, insulated aluminum, and wood/vinyl) as well as a broad range of glazing types, ranging from single pane to triple pane, with low-e and spectrally selective coatings as applicable. We estimated the energy performance characteristics of these windows (U factor and SHGC) with WINDOW 5.1 [11]. WINDOW 5.1 calculates whole-window solar and thermal properties based on the physical properties of the window frame, glazing, spacers, and gas fills. We modeled all windows using the latest model assumptions of the National Fenestration Rating Council. To ensure consistency in comparing the windows, we assumed a standard window type – casement – and the NFRC standard frame size of 60cm x 150cm. We assumed that glass was 3mm thick, and an interpane space of 12.7mm when multiple panes were used. The simulated window characteristics from WINDOW 5.1 are shown in Table 2.

We included three future window types in our database in addition to the 23 existing window technologies-material combinations. As discussed in the introduction, this paper

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[2] We used the following formulas to remove annual variation from RECS-reported energy consumption. We used heating and cooling degree day data from the census division level [10].

$\text{Heating Energy Consumption} = \text{RECS Heating Consumption} * HDD_{30\text{ Year Average}} / HDD_{1993}$
$\text{Cooling Energy Consumption} = \text{RECS Cooling Consumption} * CDD_{30\text{ Year Average}} / CDD_{1993}$

considers two possible trajectories for the development of advanced fenestration technologies: Ultra windows and Dynamic windows. These technologies were previously considered by Apte, Arasteh and Huang (2003) [5], and the properties of these windows remain unchanged from this earlier study. Since these technologies are early in their development, their energy performance characteristics were not simulated in WINDOW; rather, hypothetical values were selected that are reasonable to assume could be realized through ongoing research. Dynamic windows were not simulated directly in WINDOW (Table 2), instead, we assumed that these windows would have energy properties akin to today's best superwindows, but with variable solar heat gain coefficients.

We used the DOE2.1E energy simulation software to determine the influence that the windows described above have on annual home energy consumption. As mentioned earlier, the goal of these simulations was to determine the fraction of home energy consumption attributable to windows. In order to make this calculation applicable to the RECS homes, the simulated homes needed to be similar in construction. We accomplished this by using a set of 128 DOE-2 prototype homes derived from statistical analyses of several RECS data sets, as well as information from the National Association of Home Builders. The homes, developed by Ritschard et al. [12] , represent construction patterns for 16 geographic regions in the US defined by both political (US Census Division) and climatic (heating and cooling degree day) boundaries. As shown in Figure 1, some of these regions have been further subdivided, such that these 16 prototypes represent 20 geographic regions.

For each geographic region, Ritschard et al developed eight different prototype homes in order to reflect the diversity of local housing stock with respect to age, insulation, and size. These properties are summarized in Table 3, and detailed information about these prototypes and their modeling assumptions can be found in Ritschard et al. [12]. Note that for a given vintage of home, there may be several prototype homes to reflect variability in size and insulation levels. For each prototype home, we used a fixed area of windows assumed to represent an "average" home, distributed equally over four cardinal orientations. For pre-1970s prototypes, window area was 18-20% of heated floor area; in post-1970s prototypes, window area was 11-13% of floor area. Using regional weather data, we simulated the 25 previously-developed window types with static solar heat gain properties in all 128 homes representing 8 house types in each of 16 regions, for a total of 3,200 DOE-2 runs. The variable solar heat gain properties of the dynamic windows were then indirectly simulated by combining the heating-season energy consumption of the high-gain superwindow with the cooling season energy performance of the low-gain superwindow. For each prototype home, we then determined the fraction of heating and cooling energy consumption attributable to windows by dividing the window-related heating and cooling consumption by the total heating and cooling energy consumption, respectively[3].

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[3] We calculated the fraction of window energy consumption for heating and cooling by dividing the total space conditioning consumption attributable to windows by the whole-home space condition consumption.

From Individual Homes to National Emissions: Spreadsheet Model

In order to scale household-level data described above to the national level, we created a set of regional spreadsheet models, which we will briefly outline before explaining in greater detail. National carbon emissions due to windows were calculated in several steps. First, we assigned a DOE-2 prototype home and stock window type (see Table 2) to each home from the RECS database. Different scenarios, described below, allowed us to consider the effects of different window technologies. Second, we multiplied the RECS-reported heating and cooling energy consumption of each home by the percentage of energy consumption attributable to windows, as informed by the DOE-2 simulations. This yielded the total energy consumption attributable to windows, by fuel, for each RECS home. Throughout this process, we explicitly addressed the uncertainties associated with our assumptions through the use of a Monte Carlo analysis. These assumptions are described in more detail below. Finally, we aggregated household window-related energy consumption to the regional and national level. This was accomplished by multiplying the energy consumption of each RECS home by that home's statistically assigned "sample weight," a value calculated by the EIA which estimates the number of homes nationwide represented by the house. We then calculated regional and national *site* energy consumption by summing across all or a selection of RECS homes. Carbon emissions were calculated with the aid of fuel specific emissions factors (described below).

Assigning RECS Homes to DOE-2 Prototypes

Within our model, we assigned each home in our RECS dataset to a prototypical DOE-2 home in order to infer the performance of that home's windows. Despite the large number of prototypes used, no prototype provides an exact match in energy performance to the RECS homes, nor does the RECS survey describe every necessary parameter for modeling a home's energy consumption. Because of this, there are inherent uncertainties in matching a RECS home to a DOE-2 prototype. In order to understand the contributions of uncertainty in individual variables to the aggregate uncertainty of our model, we used a technique known as Monte Carlo analysis. Whenever a calculation involves an uncertain term, it is represented by a probability distribution which reflects the likelihood of that term being equal to a given value. Monte Carlo Analysis allows us to perform many "trials" of this calculation, each time sampling a random value from each probability distribution for each uncertain term. After a large number of trials, the result of the Monte Carlo Analysis is a probability distribution for the outcome of the calculation which reflects the uncertainties in the inputs.

We used the Monte Carlo simulation software package Crystal Ball 2000 (Decisioneering Inc, Denver, Colorado) to analyze the uncertainties associated with the home assignment process [13]. We assumed that the floor area cutoff point for the "large" prototypes (see Table 3) was uncertain and distributed normally, with a standard deviation equivalent to 10% of the prototype's design value. Since the RECS dataset only describes insulation levels as "yes" or "no", we assigned these values semi-deterministically, with a 10%

probability that the opposite value was actually true. Home age was assigned deterministically. We used information in the RECS dataset on local heating and cooling degree days combined with that home's census division to deterministically assign each home to one of the 20 climate zones shown in Figure 1.

Window Scenarios

We considered four scenarios for window thermal integrity in our model. In the "Baseline" case, homes were assigned simulated windows from our database (Table 2) consistent with their responses to the characteristics in the RECS survey. We also considered a "Current Technologies" case, a scenario where all windows in today's stock are replaced with low-e windows, a readily available high-performance product. Low-e windows comprise 40-50% of current sales, so this scenario estimates an upper bound for future energy savings that could be expected if no new window technologies were developed. Additionally, we considered two possible scenarios for the usage of emerging window technologies. In one, we considered potential energy savings if all windows were replaced with dynamic windows; in the other, we considered the potential energy savings if all windows were replaced with ultra windows with appropriate performance characteristics for their region.

Model Assumptions: Windows

Window-related model assumptions varied from scenario to scenario. Because data on window choice are exceedingly sparse, we chose to deterministically assign window properties to the RECS homes. To model the uncertainty inherent in this assignment, we added an uncertainty factor to the DOE-2 calculated window percentage of energy consumption. This is described below. In order to model the behavior of dynamic windows and storm windows (where appropriate), we assigned two window types for every RECS home: summer window and winter window. The summer window was used for calculating cooling energy performance, and the winter window was used for calculating heating energy performance. For homes with fixed window properties throughout the year, the summer and winter windows were modeled identically.

In the "Current Technologies" and "Ultra Windows" scenarios, windows were available with either low or high solar gain glazings. For each region, we simulated the glazing type that resulted in the lower annual carbon emissions, based on an a priori analysis of the data. Wherever the model predicted that both glazing technologies would result in very similar annual carbon emissions, we used the low solar gain version, as this tends to reduce peak summer electricity consumption, which is of concern to utilities and energy managers.

Model assumptions were most complex for the "Baseline" scenario; we developed an algorithm to correlate RECS – reported window properties with the database of windows shown in Table 2. In most homes, we assigned a number of glazing panes equal to the number reported in RECS. Where storm window usage was reported in RECS, we simulated a similar window with one additional pane of glass in the winter. For example, double paned with low-e plus storm window = triple pane with low-e. We assumed that storm windows were removed in the summer. The RECS survey does not differentiate between low and high solar gain glazings. We made the simplifying assumption that all low-e windows had high solar gain coatings. This does not seem unreasonable given that spectrally selective glazings did not become prevalent until the early to mid 1990s.

We simulated three frame types in WINDOW 5.1: Aluminum, Insulated Aluminum, and Wood/Vinyl. These represent the energy properties of most windows today. However, RECS does not differentiate between aluminum and insulated aluminum frames. Anecdotal evidence suggests that insulated aluminum frames captured a large market share in the central US between the mid 1970s and mid 1990s. A sensitivity analysis based [4] on this observation suggested that differentiating insulated aluminum frames from the non – insulated type would reduce total regional window energy consumption by no more than 3-5%. Based on the lack of available data and the relatively small impact of this frame type, we chose to exclude insulating aluminum frames from our model.

Modeling Energy Consumption: Uncertainties

As mentioned earlier, a lack of data prevented us from modeling uncertainty in window choice directly. This became a persistent problem: although we recognized that many aspects of our DOE-2 modeling were uncertain, the magnitudes of the uncertainties, as well as their probability distributions, were often not known. In addition to uncertainties in window *choice*, we were unsure whether individual homes would be well-represented by a model that assumes a fixed, "average" window area. To address this problem, we introduced a set of composite, random scaling factors which address uncertainties from several sources at once.

We assumed that the uncertainties in window choice and area are independent from home to home. A consequence of this is that in a large population, many of these uncertainties will cancel out as an effect of the Central Limit Theorem. However, some regions we modeled have particularly small sample sizes in RECS ($N < 100$). In these regions, uncertainties have the potential to play a larger role. For this reason, we decided to multiply the window percentage of energy consumption of each home by an independent scaling factor randomly evenly distributed between 0.85 and 1.15. Although the factorial nature of these uncertainties may have been better represented by a normal distribution due to the Central Limit Theorem, computational constraints of the software prevented us from treating this particular uncertainty in this manner.

The uncertainty that even given the appropriate window assignment, DOE-2 might not accurately calculate the percentage of energy consumption attributable to windows was also a concern. Anecdotally, DOE-2 is recognized to be less accurate in predicting total energy consumption than it is in predicting relative component loads, as well as being more accurate in predicting heating than cooling. Based on these inferences, we introduced a normally distributed scaling factor with a mean of 1.00, and a standard deviation of 0.04 for heating and 0.07 for cooling. These values are based on our estimation of the uncertainties associated with the DOE-2 model. Any errors in the

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[4] In testing the sensitivity of our model to the presence of insulated aluminum frames, we considered three possible scenarios: All aluminum frames are uninsulated (baseline), all aluminum frames are insulated, and all aluminum frames in homes built after 1970 are insulated.

DOE-2 model with respect to assigning window component loads are likely to have a large reproducible and systematic component. Therefore, for each iteration of the Monte Carlo run, we applied this uncertainty to all homes equally.

A final uncertainty associated with the DOE-2 model is the choice of heating and cooling equipment used within the model. Although the prototype homes are designed to reflect an "average" home, a given home may have space conditioning equipment more or less efficient than the prototype. While this may result in DOE-2 under- or over-predicting the absolute energy consumption of the home, we assumed that this error is equal for component loads. In most cases, then, this error cancels out when the window percentage of energy consumption is calculated. However, in the case of air conditioning, the central air conditioning system assumed in the DOE-2 prototypes may be a poor representation of the room/window air conditioning units that are prevalent in some regions. Specifically, simulations relying on a central unit may under or over-predict window energy consumption when homes are equipped with a room air conditioning unit. For homes equipped with a room air conditioning unit, we introduced an additional scaling factor for the percentage of cooling energy consumption due to windows. The methods used for calculating this factor later revealed to predict excessively low cooling consumption; however, the overall effect of this additional scaling factor is less than 2-3% of total consumption. Future efforts will remove this from the model.

In addition to uncertainties associated with the DOE-2 element of the model, the RECS-reported heating and cooling energy consumption has an uncertainty associated with it. As mentioned earlier, RECS uses a statistical model to apportion energy consumption for each fuel to a variety of end uses. Studies have shown this model to be prone to error [14]. For fossil fuels, space heating is the dominant end use. For these fuels, we scaled the reported end use for each home by a random value between 0.85 and 1.15. For electricity, however, a variety of end uses exist. Among these, heating and cooling tend to have the largest uncertainty, because they are highly temperature dependent. The result is that the aggregate energy consumption for heating and cooling combined will be less uncertain than their apportionment between heating and cooling. We represented this by scaling the whole-house RECS-reported heating electricity consumption for each home by a randomly assigned value between 0.95 and 1.05, and the total electrical cooling consumption by a random value between 0.75 and 1.25. As with the DOE-2 scaling factors, the RECS scaling factors represent our best estimates of the uncertainties associated with the reported values.

Aggregate Results: Carbon Emissions and Primary Energy Consumption

In order to convert site energy consumption into carbon emissions, we used national-average fuel-specific emissions factors for the three principal heating fuels: Natural Gas, Fuel Oil, and Liquified Petroleum Gas [15]. In contrast with these fuels, the carbon emissions factor for electricity varies widely from state to state. Although electricity emissions factors were available on a state by state basis from the EPA EGRID database[16], state boundaries did not coincide well with the geographic regions used for the rest of the analysis. With the help of GIS (Geographic Information Systems) software, we created a population-weighted average of state emissions factors for these geographic regions, as shown in Figure 2. We applied these emissions factors, with an added uncertainty of ± 5%, to the total site energy consumption for each region. This allowed us to calculate the total carbon emissions for each region. In addition to carbon emissions, we calculated primary energy consumption for each region by multiplying electricity consumption by a site-to-source efficiency factor of 3.22 [4]. For other fuels, we assumed a site-to-source efficiency factor of 1.

RESULTS AND DISCUSSION

Carbon Emissions and Energy Consumption at the National Level

The total carbon emissions and energy consumption of the scenarios we considered are presented in Figures 3 and 4, and Table 4. On a national basis, we estimate that in 1993, window-related space conditioning was responsible for 1.1 quads (quadrillion BTU) of primary energy consumption and 17 million metric tons of carbon emissions in single family residences. Monte Carlo analysis of the uncertainties explicitly considered in our model suggests that these values are accurate to within ± 3%.

Table 4 compares potential savings in emissions and consumption from the adoption of future technologies on the national level. If all windows in the 1993 housing stock were replaced with low-e, a 38% reduction in window-related carbon emissions would result. Replacement of the stock with Dynamic and Ultra windows would result in a 64% and 76% reduction in window-related carbon emissions, respectively. As can be seen in Table 4, at the national scale, results for primary energy consumption are very similar to those reported for carbon emissions.

Regional Trends

We found substantial regional variation in the carbon emissions attributable to windows. Because of the large variation in population between the individual climate regions used in this analysis, meaningful comparisons of window performance can most readily be drawn when the effects of population are removed. We therefore present the aggregate regional carbon emissions normalized to the number of single family homes in the region. We refer to these values as “per home”, but they reflect a statistically average value for a region, and the presented uncertainties do not reflect the variation between homes within the regional housing stock.

Figure 5 presents per-home carbon emissions for the different scenarios we considered. The climate regions are divided up into three groups which reflect the simulated window properties. In the “High Solar Gain” group, homes were simulated with high solar gain low-e and ultra windows. In the “Mixed Solar Gain” group, homes were simulated with low solar gain low-e windows and high solar-gain ultra windows. In the “Low Solar Gain” group, homes were simulated with low solar gain low-e and ultra windows. As can be seen in Figure 5, per-home carbon emissions attributable to the 1993 window stock varied between roughly 250 and 400 kg of carbon per year per house, with a few notable outliers. The effects of the three scenarios we considered vary among climatic zones. Figure 6 presents percentage reductions in annual carbon emissions over the existing window stock for the climate regions we studied. As this chart shows, Ultra windows offer the greatest possible emissions reductions in all climates. In climates such as those represented by Denver, San Francisco and Los Angeles, Dynamic and Ultra windows can result in emissions reductions equal to or greater than 100%. This implies that on an annual basis, in those climates, future window technologies represent a net energy benefit.

Analysis of Regional Trends

Per-home window – related emissions are a function of several factors: the energy properties of windows (U factor and SHGC), climate-dependent effects (temperature and solar intensity), and the carbon intensity of the fuel mix. In this analysis, we do not quantitatively analyze the roles of these individual factors. However, a simple description of regional window properties allows for qualitative analysis of some noteworthy outliers. Figures 7 and 8 present the regional mean U factor and SHGC, respectively.

Figure 5 shows that on a per-home basis, windows along the West Coast were responsible for significantly lower carbon emissions than in other portions of the country. As Figures 7 and 8 show, however, these regions have a relatively inefficient window stock. It seems logical, then, that the relatively mild climate in these regions and the very clean fuel mix (see Figure 2), are the primary drivers of low window carbon emissions in these regions. The existing window stock in region 10, which represents portions of the Midwest and Appalachia, is responsible for the very high per-home carbon emissions of 480 kg/yr. Given that window characteristics in this region are comparable with nearby climates, it seems that carbon-intensive electricity is primarily responsible for the large amount of annual emissions.

Figures 9 - 11 and Table 5 show simulated per-home savings in annual energy consumption over the 1993 stock from three future scenarios. The greatest energy savings from dynamic windows were seen in Texas and the southern Midwest, while the smallest savings were seen in the southwest and northern Midwest. The largest savings from ultra windows were seen in the Texas, the southern Midwest, and the northeastern US. Particularly small savings were seen in the southwest, where annual energy consumption is relatively low. In this area, predicted savings were as low as half the national average.

In contrast with regional trends in absolute emissions, much less regional variation is seen in percent savings from future window use scenarios, as shown in Figure 6. This is because these values are normalized against stock consumption, which partially removes the effect of factors dependent on climate and the fuel mix. Thus, we expect the majority of the variation in these results to be caused by window-dependent effects—either poor performance from existing window stock or exceptional performance from replacement windows. This seems to be the case with California, where savings from future window scenarios were seen to be the highest. As Figures 7 and 8 show, the existing stock in California is characterized by some of the highest U factors and SHGCs in the US. As a result, the percent improvement in performance from future windows scenarios is higher in this region, yet the low total consumption means replacement may not be economically feasible.

When the outlier data points from California are excluded, Figure 6 shows that overall patterns in predicted emissions reductions from future window scenarios are relatively consistent from region to region. Savings from ultra windows were found to be greater than those from dynamic windows in every region. However, these differences were smaller than the uncertainty within the model. One particularly surprising result was large predicted savings from dynamic windows in much of the Southwest (regions 15 – 17). Typically, this region is considered to be cooling – dominated, and we expected that the heating savings from dynamic windows would be less important. However, the region is quite diverse climatically, and analysis of the RECS data found that some areas do require significant amounts of heating. Additionally, compared with more recent homes, the older portions of the housing stock tend to require less air conditioning and more heating. This, combined with the abundant sunlight of the southwest, allows dynamic windows to perform almost as well as ultra windows.

Scaling results to 2002 building stock

The lack of available data limited our study to analyzing the 1993 window stock in single family homes. While this analysis is useful, more current numbers can be approximated simply. An analysis of the 1993 RECS dataset shows that single family homes were responsible for 72% of national primary space conditioning energy consumption. If we assume that the role of windows in total space conditioning energy consumption for single family homes is comparable to that in the building stock as a whole, then we can scale our results to represent the entire residential building stock. A simulation study of residential component loads suggests that this assumption is valid [2]. Since 1993, both housing stock size and per-home space consumption energy consumption have increased. By scaling our results by the ratio of space heating energy consumption between 2002 and 1993 we can take account for this increase[5]. Implicit in this scaling is that the energy performance of windows remains unchanged. In reality, the US window stock has become more efficient, so this estimate represents an upper bound. When all scaling factors are applied, we find that all US residential windows are responsible for approximately 1.7 quads annually. Assuming that the carbon intensity of residential space conditioning stayed roughly constant over this time period, we find that windows are responsible for about 25 million metric tons of carbon emissions annually.

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[5] We scaled our results to the entire residential building stock in year 2002 with the aid of the following formula. We used data from the DOE/EIA BTS Core Databook [3].

2002 Window Energy Consumption = (1993 Single Family Window Energy Consumption / 1993 Total Single Family Space Conditioning Energy Consumption) * 2002 Residential Sector Space Conditioning Consumption

When using these updated estimates of window energy consumption, the potential benefits of future window technologies increase. If all residential windows in the US were replaced with dynamic windows, annual energy consumption would decrease by approximately 1.1 quads, and annual carbon emissions would decrease by approximately 17 million metric tons. If ultra windows were used instead, annual energy consumption would decrease by roughly 1.3 quads, and annual carbon emissions would decrease by approximately 20 million metric tons. This would be equivalent to reducing the total US energy consumption and carbon emissions by about 1%.

Economics and Policy

It is useful to understand the economic impacts of the existing window stock in US homes, as well as the magnitude of potential cost savings from improved window technologies. Using today's approximate energy cost of $8.5 billion per quadrillion BTU, we estimate that the 1993 window stock in single family homes was responsible for $9.5 billion dollars in energy consumption annually [4]. Using our estimate for current energy consumption, we find that the entire residential window stock is responsible for $14 billion in energy consumption each year.

Future window technologies could result in significant economic benefits. If all windows in single family homes were replaced with low-e windows, annual energy savings equivalent to roughly $6 billion could be achieved on a national basis. Dynamic and ultra windows could result in annual energy cost savings of up to $9 billion and $11 billion, respectively. If we assume that a national window replacement program would encompass 100 million homes, each with 20 windows to be replaced at a cost of $400 each, cost savings from energy consumption alone would result in a simple payback time of approximately 65 years for ultra windows. This payback time would be shorter for regions with high per-home energy savings (as low as 50 years), and nearly twice as long for certain portions of the US. Ideally, programs promoting the replacement of windows would target "weak points" in the existing US window stock, where payback times are lower. There are a variety of non-economic benefits to window replacement which go beyond energy savings. These include both private benefits such as improved comfort and appearance, as well as public and environmental benefits such as decreased risk of climate change and air pollution. The latter benefits are "positive externalities", and although a detailed assessment is beyond the scope of our analysis, we submit that they make the case for window replacement considerably more compelling.

Uncertainty

We found our results to be less uncertain than we initially expected they would be. Our uncertainty in the aggregate national emissions and consumption were roughly 2-3% of the mean value. Uncertainties were larger at the regional level, ranging from 8 – 13% of the mean value. These numbers seem too small, and we believe that several factors contributed to this. We assumed that many uncertainties were independently manifested at the household level, rather than at a systematic level in the model. Because of the large number of RECS homes in our models, these uncertainties tended to cancel out as a consequence of the Central Limit Theorem. For example, we included a scaling factor of ± 15% that addressed the possibility of the wrong window being assigned to a given home. Due to the large number of homes in the model, in any given trial, a nearly equal number of homes had energy consumption values that were scaled up as down. This has the effect of "washing out" the uncertainty in the aggregate sum of energy consumption. Therefore, many potential systematic biases in our model may not have been accounted for in our uncertainty analysis. We note that uncertainties were equal for both our analysis of 1993 RECS homes and future technologies. However, the performance, adoption, and usage patterns of future technologies are all unknown and as such, uncertainties for these scenarios are likely to be far higher than we predict.

Most importantly, due to a lack of empirical data, we were forced to make educated guesses on the level of uncertainty for many terms in our model. For example, we had no data that allowed us to estimate the accuracy with which the DOE-2 prototypes predict the energy consumption of RECS homes. Because we were unable to justify many of our assumptions about uncertainty with empirical data, this limits the effectiveness of our Monte Carlo Analysis. However, because of the large number of uncertainties in our model, Monte Carlo allows us to address their interactions far more realistically than a sensitivity analysis using extreme cases. Further work will base uncertainty estimates in more empirical data and use more conservative estimates where data are not available.

Comparison with Previous Research

Frost et al [3] found that windows are responsible for 1.7 quads of energy consumption on an annual basis. In contrast to the approach used in our study, Frost estimates national energy consumption of the entire 1993 window stock by multiplying the total area of windows in the US by simulated energy intensities for a variety of window types. Scaling our 1993 findings to represent the entire US window stock, we find that windows are responsible for 1.5 quads of energy consumption. This number is roughly comparable, especially given the difference in methods between the two studies.
Using data from the BTS Core Databook [4], a summary of building energy-efficiency data compiled by the DOE Office of Building Technologies, it is possible to make a back-of-the envelope calculation for window energy efficiency. These results are presented in Apte, Arasteh and Huang (2003) and have been updated with more recent data in Appendix A. These calculations suggest that windows are responsible for 2.8 quads of energy consumption annually. This result was determined by a process quite similar to that used in this study. First, a national average for the percentage of heating and cooling loads due to windows is calculated using results from a simulation study. Second, this percentage is multiplied by the total national energy consumption. These results seem surprisingly high, given the similarity in methodologies between this approach and that used in our study. This discrepancy could arise from differing values used for both total energy consumption and the percentage of household energy consumption due to windows. However, our updated estimate of 1.7 quads for all residential windows uses the same value for total energy consumption as does the approach presented in Appendix A. Thus, the difference in results must be driven primarily by different values used for the energy consumption of windows.

The values presented in Appendix A, Table A-2, were derived from a process roughly comparable to that used in this study. The energy consumption of homes was simulated using the same 128 prototypes as this study; however a more detailed analysis was conducted which identified the sources of all loads on each home's space conditioning systems. Total loads for each building component and region were calculated by multiplying the loads for each individual prototype by the number of homes applicable to that prototype. National component loads were calculated by summing across regions. That approach finds that windows are responsible for 32% of space heating loads and 40% of space cooling loads [2]. Although we did not calculate component loads directly, we can scale the primary window energy consumption that we predict to the total primary space conditioning energy consumption reported by RECS. If we do this, we find that windows are responsible for 18% of heating energy consumption and 28% of cooling energy consumption. The cause of this difference may lie in differing approaches to simulating window energy properties between this study and the component load analysis conducted by Huang et al. While both studies use identical prototypes with equal window areas, our approach allows for much more detail in treating window energy consumption. Because our approach explicitly considers the effects of storm windows and low-e glazings, windows in our study may have, on average, lower U-factors than those assumed by Huang. Unfortunately, detailed information on the specifications of windows used by this study was not available, so it is impossible to test this hypothesis.

It is also instructive to compare our results with those from a simulation study conducted by Apte, Arasteh and Huang, which was mentioned in the introduction section. Using a database of windows identical to this study, they simulated the energy performance of dynamic and ultra windows in homes typical of today's new construction patterns. This work focused on reductions in total space heating energy consumption at the household level, not window energy consumption on the regional level, so our results should not be comparable in the absolute sense. However, the overall patterns in savings can be compared. Apte, Arasteh, and Huang concluded that low solar-gain ultra windows offer the greatest potential energy savings in the southern US, since heating energy use is relatively small compared with cooling. In the northern and central US, high solar-gain ultra windows were found to offer the greatest annual energy savings, but dynamic windows had very similar results. However, because ultra windows resulted in far greater peak cooling energy consumption in the summer, they argued that dynamic windows were desirable in these climates. We did not directly consider the effects of peak loads in our study, as only aggregate carbon emissions were of interest. If we had considered peak loads, we would expect to have found similar patterns, but with less extreme values, as air conditioning use is less common in the existing stock [2].

Overall, it is not surprising that we find ultra windows to offer the greatest potential savings in space conditioning energy consumption for existing buildings. Older buildings tend to use air conditioning less than new buildings. As a result, we found that high solar gain ultra windows come with a much lower penalty in cooling energy consumption than was found by Apte, Arasteh, and Huang for new construction. Because we specified ultra windows to be better insulated than dynamic windows, they result in lower net energy consumption in the winter. The combination of these two factors allows insulating ultra windows to offer the greatest energy savings and carbon emissions reductions on an annual basis.

Future Work

Future work will focus in three primary areas. First, as we discussed earlier, our uncertainty estimates appear to be erroneously low. We plan to refine our Monte Carlo model to remove technical errors and include more empirical data. Second, we plan to update our model of the existing window stock to include more recent window technologies, especially spectrally-selective low-e glazings. We will accomplish this by integrating the 1993 RECS dataset with more recent market/sales surveys. The result will be a more accurate assessment of the properties of current window stock. Finally, we plan to conduct a more sophisticated analysis of cost-effectiveness at the household level. This will address issues such as discount rates and cost premiums.

SUMMARY AND CONCLUSIONS

We find that on a national basis, ultra windows – very highly insulating windows – offer the greatest potential energy savings and carbon emissions reductions for the existing US window stock. If all windows were replaced with ultra windows, we predict the energy requirements and carbon emissions related to residential windows in the US could drop as much as 75%. However, dynamic windows – windows which can change their solar heat gain properties to match seasonal demands – offer energy savings nearly as large and are indistinguishable from ultra windows within the error bounds of this study. If all residential windows in the US were replaced with such windows, energy consumption and carbon emissions associated with these windows would drop by around 65%. A similar replacement using today's high performance windows – known as low-e – would result in savings roughly half as large, around 37%. Emerging fenestration technologies (dynamic and ultra windows) therefore have significant potential to reduce the energy consumption of existing US homes beyond what is possible with today's technologies. These technologies could play an important part of future efforts to retrofit the existing US housing stock for greater energy efficiency. While any program to retrofit a large portion of the US window stock will be cost-intensive, potential energy cost savings are likely to be sizeable. Given the growing risk of global climate change, increases in US household energy efficiency are likely to be necessary, and a window-retrofit program could offer long-term cost savings while reducing US carbon emissions.

While our findings suggest that the greatest energy and carbon savings in existing stock may be possible with ultra windows, it is still unclear which future fenestration technology – dynamic or ultra – would constitute the "ideal" window. Previous work suggests that dynamic windows offer optimal performance for newly-constructed homes in most regions of the United States. It is important to note that the comparison of potential benefits of these two emerging technologies is highly dependent on our assumptions regarding these technologies. Thus, our primary conclusion is that both future window technologies – dynamic and ultra windows – offer significant potential for the reduction of energy consumption and carbon emissions in the United States.

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Appendix A: A Simple Calculation to Determine the Energy Consumption of Residential Windows

Table A-1:

	U.S. Total, Quads[6]	% Attributable to Windows (see below)	U.S. Window Energy, Quads
Residential Heating	6.14	32%	1.97
Residential Cooling	1.97	40%	0.78
Total	*8.11*	-	*2.75*

Window percentages of component loads[7]

These values represent loads removed by all U.S. residential buildings' space conditioning equipment, not the primary energy consumption of this equipment. The derivation of these values can also be found in Huang et al, 1999 [2].

Table A-2:

Heating (Total = 3.99 Q)

	Quads (US)	% of Total
Conduction	-1.34	33.5%
Solar Gain	0.43	-10.7%
Infiltration / 4	-0.37	9.3%
Total Window Loads	*-1.28*	*32.1%*

Assume windows account for 1/4 of all heating and cooling infiltration loads

Cooling (Total = 1.08 Quads)

	Quads (US)	% of Total
Conduction	0.01	0.9%
Solar Gain	0.37	34.3%
Infiltration / 4	0.05	4.4%
Total Window Loads	*0.38*	*39.6%*

Assume windows account for 1/4 of all heating and cooling infiltration loads

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[6] BTS/DOE Core Databook, 2003. Table 1.2.3

[7] BTS/DOE Core Databook, 2003. Table 1.2.9