Environmental Science & Technology

pubs.acs.org/est

Article

Predicting U.S. Residential Building Energy Use and Indoor Pollutant Exposures in the Mid-21st Century

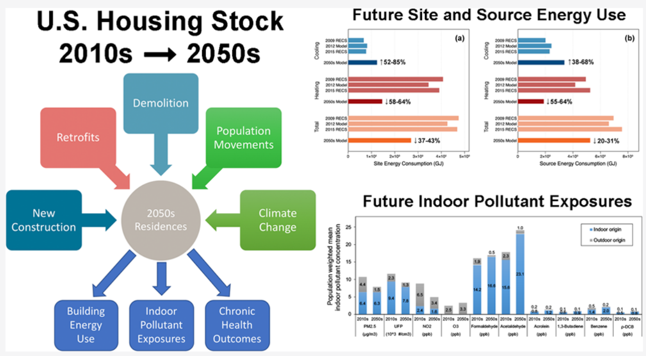
Torkan Fazli, Xinyi Dong, Joshua S. Fu, and Brent Stephens*

Cite This: *Environ. Sci. Technol.* 2021, 55, 3219−3228

Read Online

ACCESS | Metrics & More | Article Recommendations | SI Supporting Information

ABSTRACT: The extent to which climate change and other factors will influence building energy use and population exposures to indoor pollutants is not well understood. Here, we develop and apply nationally representative residential energy and indoor pollutant model sets to estimate energy use, indoor pollutant concentrations, and associated chronic health outcomes across the U.S. residential building stock in the mid-21st century. The models incorporate expected changes in meteorological and ambient air quality conditions associated with IPCC RCP 8.5 and assumptions for changes in housing characteristics and population movements while keeping other less predictable factors constant. Site and source energy consumption for residential space-conditioning are predicted to decrease by ∼37−43 and ∼20−31%, respectively, in the 2050s compared to those in a 2010s reference scenario. Population-average indoor concentrations of pollutants of ambient origin are expected to decrease, except for O_3. Holding indoor emission factors constant, indoor concentrations of pollutants with intermittent indoor sources are expected to decrease by <5% ($PM_{2.5}$) to >30% (NO_2); indoor concentrations of pollutants with persistent indoor sources (e.g., volatile organic compounds (VOCs)) are predicted to increase by ∼15−45%. We estimate negligible changes in disability-adjusted life-years (DALYs) lost associated with residential indoor pollutant exposures, well within uncertainty, although the attribution among pollutants is predicted to vary.



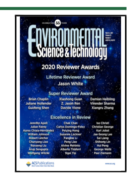
INTRODUCTION

Americans spend most of their time inside their homes[1] where they are exposed to a variety of air pollutants of both indoor and outdoor origin.[2−8] Indoor pollutant exposure is associated with both acute and chronic health outcomes.[9−11] Residential buildings also account for more than 20% of the U.S. primary energy consumption and a similar proportion of greenhouse gas emissions.[12] Residential building energy use and human exposures to indoor air pollutants will be affected by future climate change, population movements, and changes in the characteristics of the U.S. housing stock, but the likely magnitudes of influences from these factors are not well understood.

Changes in future meteorological conditions are expected to influence building energy use directly by altering heating, cooling, and ventilation loads and by changing the conditions at which heating and cooling equipment operate.[13−17] The magnitude of impacts in individual buildings is expected to vary by building type, building system characteristics, and the extent of climate changes in a building's geographic location.[18,19] The magnitude of impacts on energy use across the building stock is also expected to be influenced by changes in the underlying characteristics of the future building stock, population movements, and the magnitude and geographic distribution of changes in meteorological conditions.[20]

Climate change is also expected to impact the concentrations of indoor air pollutants inside buildings, which will have implications for human exposures and public health.[21−24] First, climate change is expected to directly influence outdoor air quality,[25,26] primarily by increasing temperatures and net radiative flux and decreasing wind speeds and planetary boundary layer heights.[27] These changes are expected to increase outdoor ozone concentrations in some locations,[28−30] which can affect indoor exposures to ozone that infiltrates indoors and ozone reaction byproducts from reactions with unsaturated organic compounds emitted indoors.[5] Conversely, the impacts of climate change on ambient particulate matter concentrations are expected to be more variable and less predictable.[31,32] Future changes in ambient particulate matter are subject to changes in both primary and precursor emissions driven by changes in energy and environmental policies implemented in response to climate change. If targeted

Received: September 18, 2020
Revised: January 26, 2021
Accepted: February 5, 2021
Published: February 16, 2021



https://dx.doi.org/10.1021/acs.est.0c06308
Environ. Sci. Technol. 2021, 55, 3219−3228

emission reductions in response to climate change concerns are successful, long-term average and peak concentrations of many outdoor pollutants are expected to decrease in many locations,[33] which is also likely to manifest as a reduction in indoor concentrations of pollutants of ambient origin because outdoor pollutants can infiltrate into buildings with varying efficiencies.[34−37]

Climate change is also expected to lead to changes in meteorological conditions that will impact building performance, operation, and human behaviors that affect both energy use and indoor pollutant concentrations, including altering air infiltration rates,[38] air-conditioner operation (which can affect pollutant filtration by central forced-air space-conditioning systems),[39−41] and window-opening behaviors.[42−45] Additionally, climate change concerns are expected to drive policy responses that influence the ways in which we design and construct buildings,[46−49] including implementing energy-efficient building practices in new construction and widespread application of energy efficiency retrofits in existing buildings.[50,51] These practices are generally expected to decrease air infiltration rates, which will tend to increase the contribution of indoor-generated pollutants and decrease the contribution of outdoor-generated pollutants.[52,53] However, the net effects of these complex interplays are unclear and have not yet been estimated at scale.

Here, we develop a set of combined building energy and indoor air quality (IAQ) models that are representative of both the current (i.e., 2010s) and future (i.e., 2050s) U.S. residential building stock. We apply the model sets using both current (i.e., 2012) and future (i.e., mid-2050s) climate and air quality scenarios to estimate the net impacts of predicted changes in meteorological conditions, ambient air quality, housing stock characteristics, and population movements on building energy use, indoor pollutant concentrations, and chronic health outcomes associated with indoor pollutant exposures in U.S. homes. The future building stock model incorporates a combination of predicted changes in predictable parameters, including future meteorological conditions, ambient air quality, the U.S. housing stock, and population movements, to provide best estimates of the site and source energy use for space-conditioning and population-average exposures to indoor pollutants in U.S. homes in the middle of the 21st century. The future building stock model holds some less predictable parameters constant such as time-averaged indoor pollutant emission rates and the predominant fuel type used in each location over time. We also incorporate model scenarios that isolate the potential impacts of changing meteorological and ambient air quality conditions alone, separate from expected changes in the U.S. housing stock and population movements.

■ MATERIALS AND METHODS

We use our previously developed residential energy and indoor air quality (REIAQ) model framework[54] as a basis for constructing a new set of combined building energy and IAQ models for both the current housing stock (as of the ~2010s) and the future housing stock (as of the ~2050s). The future stock model set accounts for expected changes in future meteorological conditions, ambient air quality, the U.S. housing stock, and population movements. The REIAQ model framework combines hourly energy simulations using BEopt version 2.2.0 and EnergyPlus version 8.1.0 with a custom single-zone hourly mass balance model for dynamic indoor pollutant simulations. The model framework is built in Python 2.7 to automate the simulation process. It uses an indirect cosimulation approach in which energy, airflow, and contaminant mass balance equations are not solved as an integrated set of equations but rather are solved sequentially.

The automated workflow involves the following sequential steps: (1) manually building a minimal number of typical home geometries in BEopt (some of which was completed in ref 54), (2) modifying those base home geometries to include region-specific details on envelope construction, heating, ventilating, and air-conditioning (HVAC) system characteristics, and other relevant characteristics for use in energy simulations, (3) running hourly energy simulations in EnergyPlus, (4) passing hourly energy simulation outputs, including modeled hourly air change rates (ACRs) resulting from infiltration and ventilation (window-opening) and central HVAC system runtimes to a transient indoor air mass balance model to simulate hourly concentrations of several priority pollutants of both indoor and outdoor origin, and (5) aggregating hourly model results over the course of the model year and applying population-weighting factors to generate estimates of population-weighted average indoor concentrations of each pollutant, as well as an aggregate estimate of the total annual heating and cooling energy consumption in U.S. residences (on both a site and source energy basis). Resulting population-average indoor pollutant concentrations are also used to generate estimates of the population-wide chronic health impacts associated with residential indoor exposures following a disability-adjusted life-years (DALYs) approach, as described in ref 9.

We built and applied this model framework for the current housing stock (2010s) and the future housing stock (2050s), as described briefly below and in detail in the Supporting Information (SI).

Baseline Year Model Set (2010s). For the 2010s model set, a total of 217 unique model home geometries that represent approximately 80% of homes in the United States were first built in BEopt using the U.S. Energy Information Administration (EIA) 2015 Residential Energy Consumption Survey (RECS) database (the latest that was available) and following a procedure similar to that described in Persily et al.[55] (Section S1, SI). The collection of 217 model homes was then used to assign baseline home model geometries across 19 of the most populous U.S. cities that also cover all ASHRAE climate zones and all 9 U.S. census divisions. These same 19 cities were used in both Fazli and Stephens[54] and Persily et al.[56] At this stage, 2012 was selected as the representative year for the 2010s model set, primarily because we had previously obtained hourly ambient air quality data[57] and actual year meteorological data[58] for each of these 19 locations in 2012. Thus, while the model set was developed to represent the housing stock as of 2015 using 2015 RECS data, the remaining inputs, including weather, air quality, and population factors, are chosen to represent the year 2012. We expect only minor discrepancies in using these two different marker years to represent the housing stock as of the ~2010s because only a small fraction of the overall housing stock was constructed between 2012 and 2015. The assignment of these baseline home models among the 19 representative cities results in a total of 4123 home models in the form of BEopt XML files (i.e., 217 homes × 19 cities = 4123 home models).

Future Model Set (2050s). By the 2050s, millions of new residential buildings will be added to the current housing stock and a smaller number of existing homes will undergo retrofits or will be demolished. The number and location of newly constructed homes between the 2010s and 2050s were estimated using population projections for 2050s[59] and making assumptions for demolition rates for existing residences (described in detail in the SI). Additionally, existing homes that are not demolished but are renovated were assumed to undergo changes in their building envelopes and/or heating and cooling systems that can affect energy use and IAQ. We defined two new categories of building vintages to represent homes built between the 2010s and 2050s: those built between 2015 and 2030 (assuming that homes built in approximately 2020 represent the entire time period) and those built between 2030 and 2050 (assuming that homes built in approximately 2040 represent the entire time period). We used projections of statewide adoption of predicted future International Energy Conservation Codes (IECCs) in each climate zone for these two representative years (i.e., 2020 and 2040) to define future housing stock characteristics such as insulation levels for exterior walls, roofs, and floors, window U-values and solar heat gain coefficients (SHGCs), and envelope air leakage. Once the home model set was updated to account for demolitions and renovations of existing homes and the construction of new homes between 2010s and 2050s, individual home models were then assigned to each of the 19 locations using projections of population movements over the same time period (Section S2, SI). For simplicity, we assumed that the predominant fuel type cited in the 2015 RECS in each location remained the predominant fuel type in the future home models as well. This resulted in a total of 8246 home models, including the original 4123 models across 19 cities assuming no demolition and new construction and another set of 4123 models accounting for demolition and new construction. The future model set represents our best estimate using the available knowledge of housing stock characteristics in the 2050s under approximately business-as-usual conditions.

Running the Models. After defining the building stock model sets, we used the automated REIAQ workflow to run energy and IAQ simulations for the current and future housing stock model set using input data for 2012 and the mid-2050s, respectively (Section S3, SI).

Meteorological Conditions. For the baseline model year, we used actual meteorological year (AMY) data for each of the modeled 19 cities for the year 2012, which was the most recent year for which hourly outdoor pollutant data were also available at the time of the development of the original REIAQ model set. For the future climate scenario, we used hourly outputs from one of the only studies of which we are aware that predicted and provided hourly weather and air quality conditions for the continental U.S. in the 2050s, using a 3 year simulation period of 2057−2059 to represent the 2050s.[60] This prior study used the Weather Research and Forecasting (WRF) model[61] with a 12 km × 12 km resolution following assumptions of the Representative Concentration Pathways (RCPs) 8.5 from the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) to simulate future weather conditions.[62] RCP 8.5 used to be recognized as a "high" emission scenario, assuming an increase in greenhouse gas emissions; however, recently, RCP 8.5 has become known more as the most realistic "business-as-usual" scenario since emissions continue to increase globally.[63] Hourly surface layer outputs from WRF (which includes the first ∼36 m above ground) were extracted from the 12 km × 12 km grid that contained the latitude and longitude of the city center for each of our 19 model cities. The average increase in ambient dry bulb temperatures across our 19 model cities is ∼2.5 °C between 2012s and 2050s (Figure S6).

Ambient Pollutant Concentrations. We used the same hourly outdoor pollutant data for the year 2012 that was used in our previous study.[37,54] Briefly, hourly outdoor pollutant data for $PM_{2.5}$, NO_2, and O_3 in each location were culled from the U.S. EPA Air Quality System (AQS) online repository for each of the 19 representative model locations for the year 2012.[57] Although this approach arbitrarily anchors the 2010s scenario to a single year (2012) for both meteorological and ambient air quality inputs, it does allow us to ensure that each hour of the simulation year was synchronized and thus as realistic as possible in the hourly simulations. Moreover, a review of the U.S. EPA's summary of ambient air quality trends reveals that 2012 was not a particularly anomalous year for air quality in the United States, with annual average concentrations of criteria pollutants $PM_{2.5}$, O_3, and NO_2 falling well within typical year-to-year trends over the late 2000s and early 2010s.[64] Ambient concentrations of several volatile organic compounds (VOCs) and aldehydes were assumed to be constant throughout the year, as hourly data are not widely available for these compounds.

For the future model years, we again used predictions of future hourly pollutant concentrations from a previous study by coauthors that predicted future hourly weather and air quality conditions for the continental United States in the 2050s (represented by a simulation period of 2057−2059) using the Community Multi-Scale Air Quality (CMAQ) modeling system version 5.0.[60] CMAQ is a three-dimensional comprehensive atmospheric chemistry and transport model developed by the EPA and the community.[65,66] Sun et al. used the same 12 km × 12 km spatial resolution as their WRF models for their CMAQ simulations to predict both hourly future meteorological conditions and pollutant concentrations, including $PM_{2.5}$, NO_2, O_3, and several VOCs and aldehydes (i.e., formaldehyde, acetaldehyde, and benzene), again assuming RCP 8.5.[60] Hourly surface layer outputs from CMAQ were obtained in the same manner as WRF outputs. For both scenarios, we estimated ambient ultrafine particle (UFP) concentrations assuming correlations between UFP and NO_x concentrations from the literature.[67] The annual average and distributions of hourly outdoor concentrations of the modeled pollutants in 2012 and the 2050s are shown in Figures S7 and S8, respectively.

Energy and IAQ Simulations. Energy and IAQ model application follow the same approach as in our previous study,[54] with nearly identical model inputs other than changes in the building stock models and future weather and climate data. Briefly, the 217 model home geometries that represent >80% of homes in the U.S. in the 2010s were first built in BEopt to generate 4123 unique XML files representing over 4123 homes across 19 cities, which were then used to generate EnergyPlus input files. EnergyPlus simulations were run for each of these home and location combinations. Python scripts were then used to gather hourly outputs from the EnergyPlus and generate hourly estimates of heating and cooling energy uses, infiltration/ventilation rates, HVAC runtimes, and other parameters. Relevant parameters from these simulations were then fed to a custom mass balance model to calculate time-varying concentrations of several pollutants of both indoor and outdoor origin that have been previously identified as being of

https://dx.doi.org/10.1021/acs.est.0c06308
Environ. Sci. Technol. 2021, 55, 3219−3228

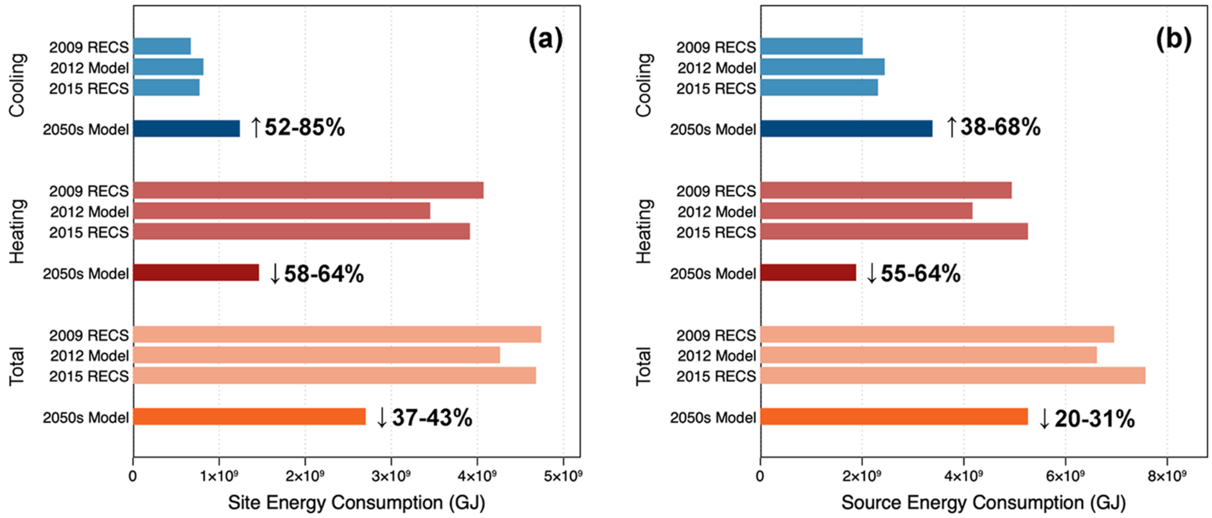


Figure 1. Predicted annual residential heating and cooling energy uses in the U.S. for the 2010s reference scenario (which includes 2012 model results and 2009/2015 RECS data) and the 2050s model set on a (a) site energy basis and (b) source energy basis.

most concern to chronic health impacts across the U.S. residential building stock. Indoor pollutant concentrations at each time step were then estimated using eq S5.

Assumptions for all pollutant source and loss mechanisms are described in the SI (Section S3.3). We used the same assumptions for indoor source strengths (both intermittent and time-averaged), pollutant penetration factors, deposition loss rate constants, and filtration efficiencies in both the current and future building stock models. We did not make any assumptions for changes in indoor pollutant source strengths in future years, primarily due to a lack of quantitative data on projections for changes in indoor emission rates over time.[68] Moreover, holding indoor source strengths constant allows for isolating the impacts of changing meteorological conditions, building stock characteristics, and outdoor pollutant concentrations in a future climate scenario. All homes were assumed to be nonsmoking across both climate scenarios. Predictions of time-varying pollutant concentrations were then summarized on an annual basis for each home, and then population-weighting factors were applied to each of the 4123 unique home models to weigh for approximately how many homes they represent across the country. Finally, the chronic health impacts of residential inhalation exposure to the modeled pollutants were estimated using a disability-adjusted life-years (DALYs) approach[9] applied to the population-weighted annual average indoor pollutant concentrations (Section S3.4, SI).

RESULTS AND DISCUSSION

Resulting estimates of the total residential heating and cooling energy uses (on a site energy basis) for the baseline model year (2012) are shown in Figure S9 along with a comparison to data from the 2009 and 2015 Residential Energy Consumption Survey (RECS). Model results for the total space-conditioning energy use in 2012 were ~9% lower and ~14% lower than the 2015 and 2009 RECS data for the U.S. housing stock, respectively, after scaling to the size of the housing stock in comparison years. The estimated site energy use for heating in 2012 was ~12% lower and ~19% lower than population-scaled 2015 and 2009 RECS data, respectively, while the estimated site energy use for cooling in 2012 was ~6% higher and ~17% higher than 2015 and 2009 RECS data, respectively.

In Table S19, we compare the number of heating degree days (HDDs) and cooling degree days (CDDs) on record for the U.S. for 2009, 2012, and 2015. The year 2012 had ~16 and ~9% fewer HDDs and ~20 and ~2% more CDDs compared to 2009 and 2015, respectively. If we assume a linear relationship between site energy use for heating/cooling and HDDs/CDDs,[69] adjusting for these differences would result in only an ~3−4% difference in site energy consumption for heating and cooling between the 2012 model results and the 2009 and 2015 EIA data, suggesting that the baseline model set estimates site energy use for the U.S. housing stock with reasonable accuracy. Given this year-to-year variability in the residential space-conditioning energy use based on weather alone, we thus define the 2010s reference scenario to include results from the model set applied for 2012 as well as 2009 and 2015 RECS data, where possible, for future energy use comparisons.

Indoor air model results for several pollutants in the baseline year (2012) are shown in Figure S10, where they are also compared to data from the existing literature on residential pollutant concentrations measured in large field studies (primarily from the United States and Canada). The 2012 model results were well within the typical magnitudes and ranges of indoor concentrations, indoor/outdoor concentration ratios, and infiltration factors as those reported in past residential field studies. Additional baseline year model results, including annual average infiltration rates, natural ventilation rates, and HVAC runtime fractions, are shown in the SI (Table S20). Estimates of DALYs lost per 100 000 persons in the baseline year are shown in Figure S11.

Figure 1 shows the estimates of site (Figure 1a) and source (Figure 1b) energy use for heating and cooling across the U.S. residential building stock for the middle of the 21st century (2050s) compared to those of the 2010s reference scenario, which includes model results for 2012 and 2009 and 2015 RECS data, taking into consideration predicted changes in the building stock, population movements, meteorological conditions, and ambient pollutant concentrations. The model set predicts site energy use; source-to-site conversion factors of 3.00 and 2.72 are used for electricity generation in the 2012s and the 2050s, respectively, based on predictions made by the

https://dx.doi.org/10.1021/acs.est.0c06308
Environ. Sci. Technol. 2021, 55, 3219−3228

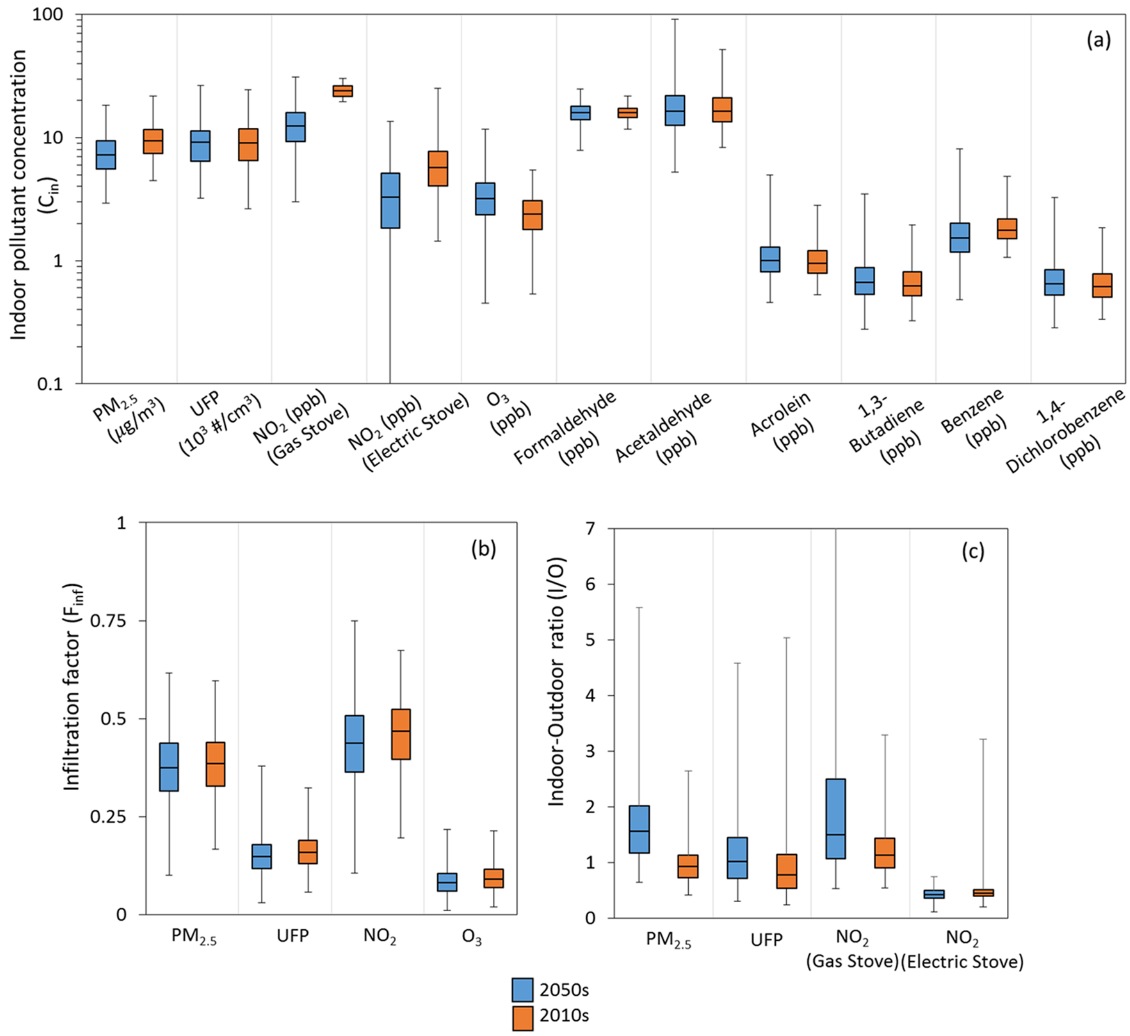


Figure 2. Distributions of model results of the annual averages of hourly (a) indoor concentrations of all modeled pollutants (on a log scale), (b) infiltration factors (F_{inf}) for $PM_{2.5}$, UFP, NO_2, and O_3, and (c) I/O ratios for $PM_{2.5}$, UFP, and NO_2 (split by homes with gas and electric stoves) for the 4123 model homes in 2012 compared to the 8246 model homes in the 2050s. Bars represent the median; boxes represent the 25th and 75th percentiles; and whiskers represent the minimum and maximum ranges.

U.S. DOE using a fossil fuel equivalency approach.[70] Model results split by the fuel type are shown in Figure S12.

Due to the combined influences of changes in climate conditions, the U.S. housing stock, and population movements, we predict that the total site and source energy consumption for space-conditioning in U.S. residences will decrease by ~37–43% (from ~(4.2–4.7) × 10^9 to ~2.7 × 10^9 GJ) and ~20–31% (from ~(6.6–7.6) × 10^9 to ~5.3 × 10^9 GJ) by mid-century (2050s) compared to those by the 2010s scenario (i.e., 2012 modeling results and 2009/2015 RECS data), respectively, driven by large decreases in heating energy use that are larger than simultaneous increases in cooling energy use in warmer climates, in addition to a greater number of people moving to warmer climate zones (Table S10).[59] We estimate that the site and source energy use for cooling will increase by ~52–85% (from ~(6.7–8.1) × 10^8 to ~1.2 × 10^9 GJ) and ~38–68% (from ~(2.0–2.4) × 10^9 to ~3.4 × 10^9 GJ) and that the site and source energy use for heating will decrease by ~58–64% (from ~(3.5–4.1) × 10^9 to ~1.5 × 10^9 GJ) and ~55–64% (from ~(4.2–5.3) × 10^9 to ~1.9 × 10^9 GJ) compared to 2012 modeling results and 2009/2015 RECS data, respectively.

The magnitude of these projected changes is fairly consistent with EIA projections for 2050 in their 2020 Annual Energy Outlook (AEO) for cooling end uses (within 11%), but we predict a much greater reduction in heating energy end uses (~68% lower).[71] Review of the assumptions in the AEO reference scenario revealed large differences in the assumed number of heating degree days (HDDs) and cooling degree days (CDDs) by 2050 compared to our assumptions (i.e., we assumed ~49% more HDD and ~95% more CDD; see Table S21), which is consistent with our use of a greater warming scenario for the 2050s than the 2020 AEO. Additionally, EIA combines historical and near-term forecasts of HDDs and CDDs with population projections to project population-weighted HDDs and CDDs using a 30 year linear trend,[72] whereas our use of climate model outputs following RCP 8.5 emission scenarios is more consistent with estimates of HDD and CDD from other similar approaches based on climate models.[15]

To account for the increased size of the housing stock expected by the middle of the 21st century, we normalized future energy estimates by the projected number of homes. The average home's site energy consumption for cooling is

https://dx.doi.org/10.1021/acs.est.0c06308
Environ. Sci. Technol. 2021, 55, 3219–3228

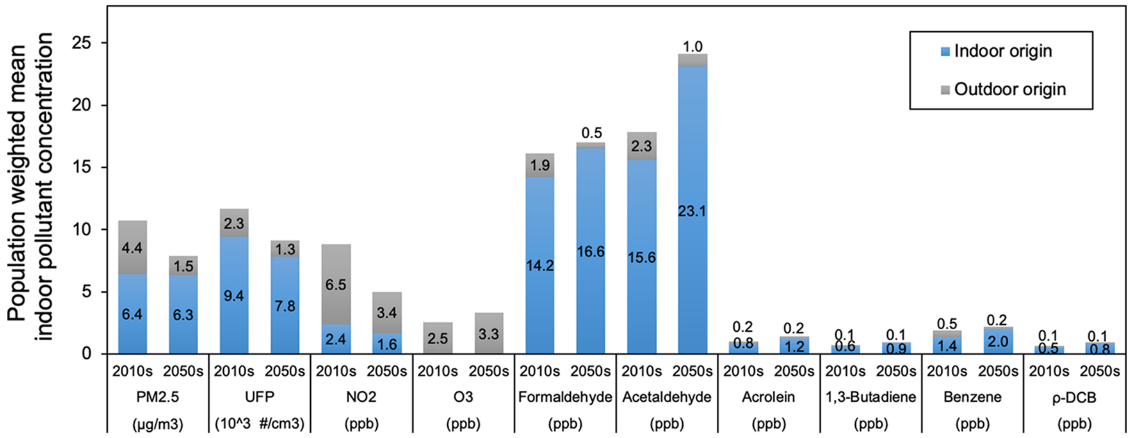


Figure 3. Population-weighted annual average indoor pollutant concentrations in 2010s and 2050s model sets.

predicted to increase by ∼22−43% from 5.9 to 6.9 GJ per home in the 2012 model and 2009/2012 RECS data to 8.4 GJ per home in the 2050s. Conversely, the average home's site energy consumption for heating is predicted to decrease by ∼66−72% from 29.2 to 35.9 GJ per home in the 2012 model and 2009/2012 RECS data to 9.9 GJ per home in the 2050s. The net change in total heating and cooling energy use is predicted to decrease by 49−56% per home in the 2050s compared to that in the 2010s reference scenario.

To isolate the impacts of only changing meteorological conditions on building energy use (i.e., climate change acting in the absence of underlying changes in the housing stock and population movements), we applied only the baseline (2010s) housing stock model with both the 2012s and 2050s weather data separately (Figure S13). Holding the 2010s housing stock constant and ignoring expected changes in population movements and housing characteristics, we estimate that the total site energy consumption of the U.S. housing stock would decrease by ∼20% in 2050s compared to that in 2012 model results, driven by an ∼36% decrease in heating energy use and an ∼45% increase in cooling energy use. Therefore, we estimate that changing climate conditions alone likely account for ∼54% of the predicted changes in the total site energy consumption of the U.S. housing stock in the 2050s scenario compared to those in 2012 model results (Figure 1) and that the underlying changes in the housing stock and population movements likely account for the remaining ∼46%. Additionally, we estimate that changing climate conditions alone likely contribute ∼82 and ∼62% to the total amount of expected changes in site energy consumption for cooling and heating, respectively, again with changes in the housing stock and population movements likely accounting for the remaining portions.

Resulting estimates of distributions of indoor pollutant concentrations, infiltration factors, and indoor/outdoor ratios for the modeled pollutants between the current (2010s) and future (2050s) housing stock are compared in Figure 2. Note that these are distributions across each home in the model sets, not yet accounting for population-weighting. Resulting estimates of outdoor air infiltration rates, ventilation rates, and HVAC system runtimes for the current and future housing stock model sets are shown in the SI (Tables S20 and S22). The average air change rate and HVAC runtime predicted for the U.S. housing stock are 0.43 per hour and 16% in the 2010s and 0.34 per hour and 20% in 2050s, respectively. In other words, we estimate an ∼21% relative reduction in outdoor air ventilation rates resulting from a combination of envelope leaks and window-opening across the housing stock due to combined changes in climate conditions, housing stock characteristics, and population movements. We also estimate an ∼25% relative increase in the HVAC system runtime with an increasing use of air-conditioning under generally warmer climate conditions across the housing stock. The combined effects of changes in the housing stock and ambient conditions yield generally lower modeled indoor pollutant concentrations in the future housing stock model set compared to those in the current housing stock model set, except for O_3 and several VOCs and aldehydes. Ambient pollutant infiltration factors (F_{inf}) are predicted to be similar between the housing stock models, but indoor/outdoor concentration ratios are predicted to be higher for $PM_{2.5}$, UFPs, and NO_2 in homes with gas stoves (but not in those with electric stoves).

Figure 3 shows the population-weighted annual average indoor pollutant concentrations predicted in the future climate scenario (2050s) compared to those in the baseline scenario (2010s). Model results for population-weighted average indoor pollutant concentrations are divided into the predicted contributions from indoor sources and from ambient (i.e., outdoor) sources. Population-weighted annual average indoor pollutant concentrations of indoor and ambient origin split by modeled home vintages are shown in the SI (Figures S14 and S15). Population-weighting accounts for the number of occupants per building archetype, as described in the Section S3.4, SI.

Ambient concentrations of most pollutants of ambient origin are predicted to decrease in the future with the expectation of increasing emission controls by the 2050s. A projected decrease in ambient pollutant concentrations combines with a projected reduction in air infiltration rates to contribute to a decrease in indoor concentrations of those ambient-infiltrated pollutants, on average. One notable exception is ozone, which is expected to increase in future climate scenarios,[60] thereby increasing the amount of ozone that infiltrates and persists in homes.

For pollutants with primarily intermittent indoor sources but that are not greatly affected by the type of fuel used in buildings (e.g., $PM_{2.5}$ and UFPs, each primarily assumed to be from cooking sources regardless of fuel), population-weighted average indoor concentrations are expected to slightly decrease in future climate scenarios (i.e., 1.5% for $PM_{2.5}$ and 7.5% for

https://dx.doi.org/10.1021/acs.est.0c06308
Environ. Sci. Technol. 2021, 55, 3219−3228

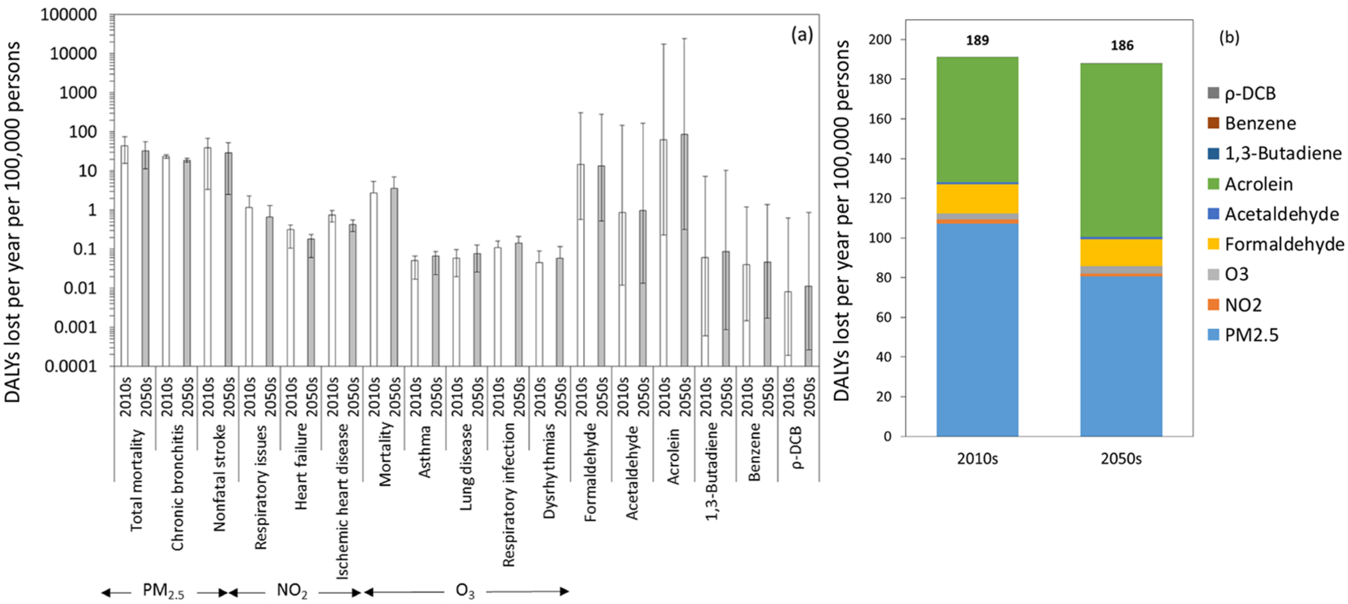


Figure 4. Estimates of annual DALYs lost per 100 000 persons in U.S. residences in the 2010s and 2050s model sets, made using the IND and ID approaches from Logue et al.[9] The bars in (a) indicate the estimated DALYs lost attributable to pollutant exposure and health end point, and the whiskers show uncertainty (95% CI bounds), and (b) shows a summation of the central estimates of DALYs lost by pollutant exposure and without uncertainty for clarity.

UFPs). This is due in part to slight differences in emission rates resulting from an expected increase in the number of homes with electric stoves rather than gas stoves, with smaller impacts resulting from small changes in predicted infiltration and ventilation (i.e., window-opening) conditions based on both climate and building stock changes. Larger reductions in population-weighted average indoor concentrations are predicted for NO_2 (i.e., ∼31%). This is primarily due to an expected increase in the number of homes with electric stoves rather than gas stoves, again with smaller impacts resulting from small changes in predicted infiltration and ventilation conditions based on both climate and building stock changes.

For those pollutants with persistent indoor sources (e.g., VOCs and aldehydes), moderate to large increases in population-weighted average indoor concentrations are predicted by mid-century. This includes a ∼15% increase in formaldehyde concentrations and a ∼45% increase in acetaldehyde, acrolein, benzene, and other VOC concentrations. These effects are primarily due to the predicted impacts of climate change in future years on reducing infiltration and ventilation rates via a combination of changing meteorological driving forces and also a changing housing stock and movements (i.e., more people moving into greater numbers of tighter homes).

To explore the effects of these different, and sometimes competing, factors that contribute to the predicted changes in residential indoor pollutant concentrations in the 2050s scenario, we ran two intermediate scenarios within the context of the 2010s and 2050s scenarios. These include one scenario (2050s-Alt #1) that uses the 2010s housing stock model, 2010s population distribution, and 2010s outdoor pollutant concentrations, but with 2050s meteorological conditions applied to infer the influence of future climate alone, and one scenario (2050s-Alt #2) that uses the 2010s housing stock model and 2010s population distribution applied with 2050s outdoor pollutant concentrations and 2050s meteorological conditions to infer the influence of future climate and future ambient air quality (Figure S16). The first additional comparison reveals that changing meteorological conditions alone and holding all other factors constant would lead to a small (∼6−14%) decrease in the annual average indoor concentrations of pollutants of indoor origin and a corresponding increase in indoor concentrations of pollutants of outdoor origin. Both of these influences are due to slightly increased air change rates among the existing housing stock (and the net magnitude of impacts would vary by pollutant). The second additional comparison reveals that the net effects of changing both future meteorological conditions and ambient air quality, again holding the housing stock and population distribution constant, would be a decrease of between 13 and 34% in the annual average indoor concentrations of all pollutants except for O_3, which would increase due to expected increases in ambient concentrations.

Figure 4 shows estimates of disability-adjusted life-years (DALYs) lost per 100 000 residents due to long-term inhalation of indoor air pollutants in U.S. residences for the baseline housing stock (2010s) and the future housing stock (2050s). The total number of DALYs lost across the population is predicted to be similar between current and future climate scenarios: ∼189 per 100 000 persons in the 2010s and ∼186 per 100 000 persons in the 2050s, well within the large ranges of uncertainty for these estimates. However, the attribution among pollutants is predicted to vary, with lower $PM_{2.5}$ exposures leading to ∼25% fewer DALYs lost but higher exposures to VOCs of indoor origin (especially acrolein) leading to ∼30% more DALYs lost.

While past perspectives and reviews have articulated how climate change is likely to affect the indoor environment and occupant health, in addition to influencing building energy consumption, no studies of which we are aware to date have provided quantitative estimates of the likely impacts of climate change on all three of these metrics, indoor air quality, human health outcomes, and building energy use, across representative housing stocks. By combining realistic predictions of future

https://dx.doi.org/10.1021/acs.est.0c06308
Environ. Sci. Technol. 2021, 55, 3219−3228

meteorological conditions, ambient air quality, housing stock characteristics, and population movements, we provide a realistic assessment of the likely combined influences of these factors on site and source building energy use and indoor pollutant exposures and long-term health outcomes in U.S. residences. We also isolate the impacts of predicted changes in meteorological and ambient air quality conditions alone using model scenarios that hold other factors constant.

Overall, we estimate that site and source energy use for space-conditioning in U.S. residences will decrease by ~37−43 and ~20−31%, respectively, by the 2050s compared to those by the 2010s under the assumptions of IPCC RCP 8.5. While these results may be counterintuitive, they do not eliminate the need to switch to low-carbon renewable energy resources to address climate change, as the magnitude of predicted differences is not large compared to what decarbonization of the U.S. energy mix could achieve.[73] We also estimate that population-average indoor pollutant exposures are expected to decrease for some pollutants (especially those with substantial outdoor sources that infiltrate indoors) but increase for others (especially those with predominant indoor sources). However, the net impacts on long-term health outcomes are predicted to be negligible because the changing attribution among different pollutants balances each other. Moreover, the predicted increases in population-average indoor concentrations of pollutants of primarily indoor origin demonstrate the importance of prioritizing widespread efforts to reduce indoor sources through indoor emission controls, improving ventilation, and implementing effective air cleaning and filtration strategies to further reduce the chronic health burden of indoor air pollutant exposures in U.S. residences.

There are several important limitations to this work worth noting and improving upon in future work. For one, we rely on a narrow range of hourly meteorological and ambient air quality inputs in both the baseline/reference year (i.e., 2012 representing ~2010s) and the projected years (i.e., 2057−2059 representing the 2050s); we do not explore other scenarios such as longer-term projections[15] or those that consider the influences of urban land expansion.[74,75] Second, the future housing stock model and climate and air quality models are not intrinsically linked but rather aggregate across disparate models; linked models could improve the overall accuracy and abilities to explore various policy scenarios. Third, we produce a deterministic rather than stochastic set of outcomes, rooted in population-average assumptions for model input parameters that do not provide insight into the uncertainties inherent in our predictions. Fourth, we hold some input parameters constant even if they are likely to vary in future years. For example, whole-house-specific VOC emission rates are almost certain to vary over time, but they are likely to vary in a way that is unpredictable and therefore challenging to incorporate in the future housing stock models. Finally, we rely on well-mixed single-zone mass balance models for concentration estimates rather than multizone airflow and contaminant transport and dynamic human behavior models.

While these assumptions and decisions allow for making quantitative comparisons within a limited set of available resources, future work should prioritize the following improvements. For one, the housing stock, meteorological, and ambient air quality models could be mechanistically linked. Second, stochastic inputs could be incorporated to generate likely ranges of outcomes and uncertainties even within a set of climate scenario assumptions. Third, a range of plausible policy scenarios could be incorporated that influence future housing stock characteristics, meteorological conditions, and ambient air quality, including aggressive climate action (e.g., widespread electrification, adoption of more stringent energy codes, deep energy retrofit incentives, etc.) and the introduction of IAQ interventions such as air cleaners, high-efficiency HVAC filtration, and/or mechanical ventilation.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.0c06308.

Full details of the methodology and additional detailed results (PDF)

AUTHOR INFORMATION

Corresponding Author

Brent Stephens − *Department of Civil, Architectural, and Environmental Engineering, Illinois Institute of Technology, Chicago, Illinois 60616, United States;* orcid.org/0000-0002-0177-6703; Email: brent@iit.edu

Authors

Torkan Fazli − *Department of Civil, Architectural, and Environmental Engineering, Illinois Institute of Technology, Chicago, Illinois 60616, United States*

Xinyi Dong − *Department of Civil and Environmental Engineering, University of Tennessee, Knoxville, Knoxville, Tennessee 37996, United States*

Joshua S. Fu − *Department of Civil and Environmental Engineering, University of Tennessee, Knoxville, Knoxville, Tennessee 37996, United States; Computational Earth Sciences Group, Computational Sciences and Engineering Division, Oak Ridge National Laboratory, Oak Ridge, Tennessee 37831, United States;* orcid.org/0000-0001-5464-9225

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.est.0c06308

Author Contributions

T.F. and B.S. conceived the research. T.F. developed and applied the housing stock model. J.S.F and X.D. developed and applied the future climate and air quality model and provided hourly outputs. T.F. and B.S. wrote the paper. All authors reviewed and edited the paper.

Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

This work was supported by the U.S. Environmental Protection Agency under Assistance Agreement no. 83575001 awarded to the Illinois Institute of Technology. It has not been formally reviewed by EPA.

REFERENCES

(1) Klepeis, N. E.; Nelson, W. C.; Ott, W. R.; Robinson, J. P.; Tsang, A. M.; Switzer, P.; Behar, J. V.; Hern, S. C.; Engelmann, W. H. The National Human Activity Pattern Survey (NHAPS): A Resource for Assessing Exposure to Environmental Pollutants. *J. Exposure Sci. Environ. Epidemiol.* **2001**, *11*, 231−252.

(2) Sax, S. N.; Bennett, D. H.; Chillrud, S. N.; Kinney, P. L.; Spengler, J. D. Differences in Source Emission Rates of Volatile

Organic Compounds in Inner-City Residences of New York City and Los Angeles. *J. Exposure Sci. Environ. Epidemiol.* **2004**, *14*, S95−S109.
(3) Meng, Q. Y.; Turpin, B. J.; Korn, L.; Weisel, C. P.; Morandi, M.; Colome, S.; Zhang, J.; Stock, T.; Spektor, D.; Winer, A.; Zhang, L.; Lee, J. H.; Giovanetti, R.; Cui, W.; Kwon, J.; Alimokhtari, S.; Shendell, D.; Jones, J.; Farrar, C.; Maberti, S. Influence of Ambient (Outdoor) Sources on Residential Indoor and Personal PM2.5 Concentrations: Analyses of RIOPA Data. *J. Exposure Sci. Environ. Epidemiol.* **2005**, *15*, 17−28.
(4) Wallace, L.; Williams, R. Use of Personal-Indoor-Outdoor Sulfur Concentrations to Estimate the Infiltration Factor and Outdoor Exposure Factor for Individual Homes and Persons. *Environ. Sci. Technol.* **2005**, *39*, 1707−1714.
(5) Weschler, C. J. Ozone's Impact on Public Health: Contributions from Indoor Exposures to Ozone and Products of Ozone-Initiated Chemistry. *Environ. Health Perspect.* **2006**, *114*, 1489−1496.
(6) Wallace, L.; Ott, W. Personal Exposure to Ultrafine Particles. *J. Exposure Sci. Environ. Epidemiol.* **2011**, *21*, 20−30.
(7) Logue, J. M.; McKone, T. E.; Sherman, M. H.; Singer, B. C. Hazard Assessment of Chemical Air Contaminants Measured in Residences. *Indoor Air* **2011**, *21*, 92−109.
(8) Azimi, P.; Stephens, B. A Framework for Estimating the US Mortality Burden of Fine Particulate Matter Exposure Attributable to Indoor and Outdoor Microenvironments. *J. Exposure Sci. Environ. Epidemiol.* **2020**, *30*, 271−284.
(9) Logue, J. M.; Price, P. N.; Sherman, M. H.; Singer, B. C. A Method to Estimate the Chronic Health Impact of Air Pollutants in U.S. Residences. *Environ. Health Perspect.* **2012**, *120*, 216−222.
(10) Jones, A. Indoor Air Quality and Health. *Atmos. Environ.* **1999**, *33*, 4535−4564.
(11) ASHRAE. *ASHRAE Position Document on Indoor Air Quality*; American Society of Heating, Refrigerating and Air-Conditioning Engineers: 2020.
(12) EIA. *Buildings Energy Data Book: New Residential Buildings Construction and Companies*; Institute for Energy and Environmental Research, 2011. https://www.eia.gov/tools/faqs/faq.php?id=86&t=1.%20US%20EIA%20FAQ%20%E2%80%9CHow%20much%20energy%20is%20consumed%20in%20U.S.%20buildings?%E2%80%9D (accessed Oct 17, 2011).
(13) Wang, H.; Chen, Q. Impact of Climate Change Heating and Cooling Energy Use in Buildings in the United States. *Energy Build.* **2014**, *82*, 428−436.
(14) Dirks, J. A.; Gorrissen, W. J.; Hathaway, J. H.; Skorski, D. C.; Scott, M. J.; Pulsipher, T. C.; Huang, M.; Liu, Y.; Rice, J. S. Impacts of Climate Change on Energy Consumption and Peak Demand in Buildings: A Detailed Regional Approach. *Energy* **2015**, *79*, 20−32.
(15) Petri, Y.; Caldeira, K. Impacts of Global Warming on Residential Heating and Cooling Degree-Days in the United States. *Sci. Rep.* **2015**, *5*, No. 12427.
(16) Güneralp, B.; Zhou, Y.; Ürge-Vorsatz, D.; Gupta, M.; Yu, S.; Patel, P. L.; Fragkias, M.; Li, X.; Seto, K. C. Global Scenarios of Urban Density and Its Impacts on Building Energy Use through 2050. *Proc. Natl. Acad. Sci. U.S.A.* **2017**, *114*, 8945−8950.
(17) Li, D. H. W.; Yang, L.; Lam, J. C. Impact of Climate Change on Energy Use in the Built Environment in Different Climate Zones − A Review. *Energy* **2012**, *42*, 103−112.
(18) Huang, J.; Gurney, K. R. The Variation of Climate Change Impact on Building Energy Consumption to Building Type and Spatiotemporal Scale. *Energy* **2016**, *111*, 137−153.
(19) Huang, J.; Gurney, K. R. Impact of Climate Change on U.S. Building Energy Demand: Sensitivity to Spatiotemporal Scales, Balance Point Temperature, and Population Distribution. *Clim. Change* **2016**, *137*, 171−185.
(20) Zhou, Y.; Clarke, L.; Eom, J.; Kyle, P.; Patel, P.; Kim, S. H.; Dirks, J.; Jensen, E.; Liu, Y.; Rice, J.; Schmidt, L.; Seiple, T. Modeling the Effect of Climate Change on U.S. State-Level Buildings Energy Demands in an Integrated Assessment Framework. *Appl. Energy* **2014**, *113*, 1077−1088.
(21) IOM. *Climate Change, the Indoor Environment, and Health*; Committee on the Effect of Climate Change on Indoor Air Quality and Public Health, Institute of Medicine: Washington, DC, 2011.
(22) Spengler, J. D. Climate Change, Indoor Environments, and Health: Editorial. *Indoor Air* **2012**, *22*, 89−95.
(23) Nazaroff, W. W. Exploring the Consequences of Climate Change for Indoor Air Quality. *Environ. Res. Lett.* **2013**, *8*, No. 015022.
(24) Vardoulakis, S.; Dimitroulopoulou, C.; Thornes, J.; Lai, K.-M.; Taylor, J.; Myers, I.; Heaviside, C.; Mavrogianni, A.; Shrubsole, C.; Chalabi, Z.; Davies, M.; Wilkinson, P. Impact of Climate Change on the Domestic Indoor Environment and Associated Health Risks in the UK. *Environ. Int.* **2015**, *85*, 299−313.
(25) Lelieveld, J.; Evans, J. S.; Fnais, M.; Giannadaki, D.; Pozzer, A. The Contribution of Outdoor Air Pollution Sources to Premature Mortality on a Global Scale. *Nature* **2015**, *525*, 367−371.
(26) Silva, R. A.; West, J. J.; Zhang, Y.; Anenberg, S. C.; Lamarque, J.-F.; Shindell, D. T.; Collins, W. J.; Dalsoren, S.; Faluvegi, G.; Folberth, G.; Horowitz, L. W.; Nagashima, T.; Naik, V.; Rumbold, S.; Skeie, R.; Sudo, K.; Takemura, T.; Bergmann, D.; Cameron-Smith, P.; Cionni, I.; Doherty, R. M.; Eyring, V.; Josse, B.; MacKenzie, I. A.; Plummer, D.; Righi, M.; Stevenson, D. S.; Strode, S.; Szopa, S.; Zeng, G. Global Premature Mortality Due to Anthropogenic Outdoor Air Pollution and the Contribution of Past Climate Change. *Environ. Res. Lett.* **2013**, *8*, No. 034005.
(27) Penrod, A.; Zhang, Y.; Wang, K.; Wu, S.-Y.; Leung, L. R. Impacts of Future Climate and Emission Changes on U.S. Air Quality. *Atmos. Environ.* **2014**, *89*, 533−547.
(28) Bell, M.; Goldberg, R.; Hogrefe, C.; Kinney, P.; Knowlton, K.; Lynn, B.; Rosenthal, J.; Rosenzweig, C.; Patz, J. Climate Change, Ambient Ozone, and Health in 50 US Cities. *Clim. Change* **2007**, *82*, 61−76.
(29) Jacob, D. J.; Winner, D. A. Effect of Climate Change on Air Quality. *Atmos. Environ.* **2009**, *43*, 51−63.
(30) Racherla, P. N.; Adams, P. J. U.S. Ozone Air Quality under Changing Climate and Anthropogenic Emissions. *Environ. Sci. Technol.* **2009**, *43*, 571−577.
(31) Tagaris, E.; Liao, K.-J.; DeLucia, A. J.; Deck, L.; Amar, P.; Russell, A. G. Potential Impact of Climate Change on Air Pollution-Related Human Health Effects. *Environ. Sci. Technol.* **2009**, *43*, 4979−4988.
(32) Penrod, A.; Zhang, Y.; Wang, K.; Wu, S.-Y.; Leung, L. R. Impacts of Future Climate and Emission Changes on U.S. Air Quality. *Atmos. Environ.* **2014**, 533−547.
(33) Tagaris, E.; Manomaiphiboon, K.; Liao, K.-J.; Leung, L. R.; Woo, J.-H.; He, S.; Amar, P.; Russell, A. G. Impacts of Global Climate Change and Emissions on Regional Ozone and Fine Particulate Matter Concentrations over the United States. *J. Geophys. Res.* **2007**, *112*, No. D14312.
(34) Kearney, J.; Wallace, L.; MacNeill, M.; Xu, X.; VanRyswyk, K.; You, H.; Kulka, R.; Wheeler, A. J. Residential Indoor and Outdoor Ultrafine Particles in Windsor, Ontario. *Atmos. Environ.* **2011**, *45*, 7583−7593.
(35) MacNeill, M.; Wallace, L.; Kearney, J.; Allen, R. W.; Van Ryswyk, K.; Judek, S.; Xu, X.; Wheeler, A. Factors Influencing Variability in the Infiltration of PM2.5 Mass and Its Components. *Atmos. Environ.* **2012**, *61*, 518−532.
(36) Stephens, B. Building Design and Operational Choices That Impact Indoor Exposures to Outdoor Particulate Matter inside Residences. *Sci. Technol. Built Environ.* **2015**, *21*, 3−13.
(37) Chen, C.; Zhao, B. Review of Relationship between Indoor and Outdoor Particles: I/O Ratio, Infiltration Factor and Penetration Factor. *Atmos. Environ.* **2011**, *45*, 275−288.
(38) Ilacqua, V.; Dawson, J.; Breen, M.; Singer, S.; Berg, A. Effects of Climate Change on Residential Infiltration and Air Pollution Exposure. *J. Exposure Sci. Environ. Epidemiol.* **2017**, 16−23.
(39) Stephens, B.; Siegel, J. A.; Novoselac, A. Operational Characteristics of Residential and Light-Commercial Air-Condition-

https://dx.doi.org/10.1021/acs.est.0c06308
Environ. Sci. Technol. 2021, 55, 3219−3228

ing Systems in a Hot and Humid Climate Zone. *Build. Environ.* **2011**, *46*, 1972−1983.
(40) Touchie, M. F.; Siegel, J. A. Residential HVAC Runtime from Smart Thermostats: Characterization, Comparison, and Impacts. *Indoor Air* **2018**, *28*, 905−915.
(41) Thornburg, J. W.; Rodes, C. E.; Lawless, P. A.; Stevens, C. D.; Williams, R. W. A Pilot Study of the Influence of Residential HAC Duty Cycle on Indoor Air Quality. *Atmos. Environ.* **2004**, *38*, 1567−1577.
(42) Wallace, L. A.; Emmerich, S. J.; Howard-Reed, C. Continuous Measurements of Air Change Rates in an Occupied House for 1 Year: The Effect of Temperature, Wind, Fans, and Windows. *J. Exposure Sci. Environ. Epidemiol.* **2002**, *12*, 296−306.
(43) Howard-Reed, C.; Wallace, L. A.; Ott, W. R. The Effect of Opening Windows on Air Change Rates in Two Homes. *J. Air Waste Manage. Assoc.* **2002**, *52*, 147−159.
(44) Marr, D.; Mason, M.; Mosley, R.; Liu, X. The Influence of Opening Windows and Doors on the Natural Ventilation Rate of a Residential Building. *HVACR Res.* **2012**, *18*, 195−203.
(45) Johnson, T.; Long, T. Determining the Frequency of Open Windows in Residences: A Pilot Study in Durham, North Carolina during Varying Temperature Conditions. *J. Exposure Sci. Environ. Epidemiol.* **2005**, *15*, 329−349.
(46) Ürge-Vorsatz, D.; Danny Harvey, L. D.; Mirasgedis, S.; Levine, M. D. Mitigating CO2 Emissions from Energy Use in the World's Buildings. *Build. Res. Inf.* **2007**, *35*, 379−398.
(47) Langevin, J.; Harris, C. B.; Reyna, J. L. Assessing the Potential to Reduce U.S. Building CO2 Emissions 80% by 2050. *Joule* **2019**, 2403−2424.
(48) Farese, P. Technology: How to Build a Low-Energy Future. *Nature* **2012**, *488*, 275−277.
(49) Kennedy, C. A.; Ibrahim, N.; Hoornweg, D. Low-Carbon Infrastructure Strategies for Cities. *Nat. Clim. Change* **2014**, *4*, 343−346.
(50) Tonn, B.; Rose, E.; Schmoyer, R.; Eisenberg, J.; Ternes, M.; Schweitzer, M.; Hendrick, T. *Evaluation of the National Weatherization Assistance Program during Program Years 2009−2011 (American Reinvestment and Recovery Act Period)*, ORNL/TM-2011/87; Oak Ridge National Laboratory: Oak Ridge, TN, 2011.
(51) Bradshaw, J. L.; Bou-Zeid, E.; Harris, R. H. Comparing the Effectiveness of Weatherization Treatments for Low-Income, American, Urban Housing Stocks in Different Climates. *Energy Build.* **2014**, *69*, 535−543.
(52) Shrestha, P. M.; Humphrey, J. L.; Barton, K. E.; Carlton, E. J.; Adgate, J. L.; Root, E. D.; Miller, S. L. Impact of Low-Income Home Energy-Efficiency Retrofits on Building Air Tightness and Healthy Home Indicators. *Sustainability* **2019**, *11*, No. 2667.
(53) Nabinger, S.; Persily, A. Impacts of Airtightening Retrofits on Ventilation Rates and Energy Consumption in a Manufactured Home. *Energy Build.* **2011**, *43*, 3059−3067.
(54) Fazli, T.; Stephens, B. Development of a Nationally Representative Set of Combined Building Energy and Indoor Air Quality Models for U.S. Residences. *Build. Environ.* **2018**, *136*, 198−212.
(55) Persily, A. K.; Musser, A.; Leber, D. *A Collection of Homes to Represent the U.S. Housing Stock*, NISTIR 7330; National Institute of Standards and Technology (NIST): Gaithersburg, MD, 2006.
(56) Persily, A.; Musser, A.; Emmerich, S. J. Modeled Infiltration Rate Distributions for U.S. Housing. *Indoor Air* **2010**, *20*, 473−485.
(57) U.S. EPA. *Download Detailed AQS Data*; Technology Transfer Network (TTN) Air Quality System (AQS), 2013.
(58) White Box Technologies. *Weather Data for Energy Calculations: Historical Data*; White Box Technologies Inc., 2015.
(59) ProximityOne. http://proximityone.com.
(60) Sun, J.; Fu, J. S.; Huang, K.; Gao, Y. Estimation of Future PM2.5- and Ozone-Related Mortality over the Continental United States in a Changing Climate: An Application of High-Resolution Dynamical Downscaling Technique. *J. Air Waste Manage. Assoc.* **2015**, *65*, 611−623.
(61) Skamarock, W. C.; Klemp, J. B. A Time-Split Nonhydrostatic Atmospheric Model for Weather Research and Forecasting Applications. *J. Comput. Phys.* **2008**, *227*, 3465−3485.
(62) Gao, Y.; Fu, J. S.; Drake, J. B.; Liu, Y.; Lamarque, J.-F. Projected Changes of Extreme Weather Events in the Eastern United States Based on a High Resolution Climate Modeling System. *Environ. Res. Lett.* **2012**, *7*, No. 044025.
(63) Troup, L.; Fannon, D. In *Morphing Climate Data to Simulate Building Energy Consumption*, ASHRAE and IBPSA-USA SimBuild 2016: Building Performance Modeling Conference, 2016; p 1.
(64) U.S. EPA. *National Air Quality: Status and Trends of Key Air Pollutants. Air Quality Trends*; United States Environmental Protection Agency, 2020.
(65) Tesche, T. W.; Morris, R.; Tonnesen, G.; McNally, D.; Boylan, J.; Brewer, P. CMAQ/CAMx Annual 2002 Performance Evaluation over the Eastern US. *Atmos. Environ.* **2006**, *40*, 4906−4919.
(66) Lam, Y. F.; Fu, J. S.; Wu, S.; Mickley, L. J. Impacts of Future Climate Change and Effects of Biogenic Emissions on Surface Ozone and Particulate Matter Concentrations in the United States. *Atmos. Chem. Phys.* **2011**, *11*, 4789−4806.
(67) Azimi, P.; Zhao, D.; Stephens, B. Modeling the Impact of Residential HVAC Filtration on Indoor Particles of Outdoor Origin (RP-1691). *Sci. Technol. Built Environ.* **2016**, *22*, 431−462.
(68) Weschler, C. J. Changes in Indoor Pollutants since the 1950s. *Atmos. Environ.* **2009**, *43*, 153−169.
(69) Isaac, M.; van Vuuren, D. P. Modeling Global Residential Sector Energy Demand for Heating and Air Conditioning in the Context of Climate Change. *Energy Policy* **2009**, *37*, 507−521.
(70) Donohoo-Vallett, P. *Accounting Methodology for Source Energy of Non-Combustible Renewable Electricity Generation*; U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, 2016.
(71) EIA. *Annual Energy Outlook 2020. Table 4. Residential Sector Key Indicators and Consumption*; U.S. Energy Information Administration, 2020.
(72) EIA. *Annual Energy Outlook 2020. Buildings*; U.S. Energy Information Administration, 2020.
(73) Langevin, J.; Harris, C. B.; Reyna, J. L. Assessing the Potential to Reduce U.S. Building CO2 Emissions 80% by 2050. *Joule* **2019**, *3*, 2403−2424.
(74) Huang, K.; Li, X.; Liu, X.; Seto, K. C. Projecting Global Urban Land Expansion and Heat Island Intensification through 2050. *Environ. Res. Lett.* **2019**, *14*, No. 114037.
(75) Krayenhoff, E. S.; Moustaoui, M.; Broadbent, A. M.; Gupta, V.; Georgescu, M. Diurnal Interaction between Urban Expansion, Climate Change and Adaptation in US Cities. *Nat. Clim. Change* **2018**, *8*, 1097−1103.

https://dx.doi.org/10.1021/acs.est.0c06308
Environ. Sci. Technol. 2021, 55, 3219−3228