Material flows and GHG emissions from housing stock evolution in US counties, 2020–60

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ABSTRACT

The evolution of housing stocks determines demand for construction materials and energy, and associated emissions of greenhouse gasses (GHGs). The contribution of construction to building life-cycle emissions is growing as buildings become more energy efficient and the energy supply decarbonizes. A housing stock model is developed for counties in the United States using dynamic vacancy rates which endogenously influence stock out- and inflows. Stocks of three house types and 10 construction cohorts are projected for all contiguous US counties for the period 2020–60. Inflows and outflows of construction materials are then estimated along with GHG emissions associated with material production and construction activities in scenarios defined by stock turnover rates, population share by house type, and floor area characteristics of new houses. The results provide new insights into the drivers of construction-related emissions at local and national levels, and identify opportunities for their reduction. Demolition material flows grow in relation to construction material flows over the analysis period. Increasing the stock turnover rate increases future floor area per person, material requirements, and emissions from construction. Scenarios with reduced floor area and more multifamily homes in new construction have lower floor area growth, material requirements, and emissions from construction.

POLICY RELEVANCE

Housing construction constitutes an important share of annual residential GHG emissions in the US. The characteristics of new construction also influence residential energy use over longer time periods. Increasing the share of multifamily housing in construction and reducing the average size of new single-family homes by eliminating very large homes are two strategies that can reliably and substantially reduce the environmental burdens of new construction. These same strategies would limit or, if combined, reverse the growth of residential floor area per person, enabling reductions of energy-related emissions. Policymakers can therefore reduce residential sector emissions in the short and long terms by encouraging the supply of multifamily homes and smaller housing typologies, and limiting construction of large homes.

1. INTRODUCTION

Buildings are a major contributor to anthropogenic greenhouse gas (GHG) emissions. The extent to which emissions can be reduced from both the construction and operation of buildings will play a key role in determining the feasibility of achieving ambitious climate change mitigation targets (Krausmann *et al.* 2020). As building stocks evolve through construction and demolition, they require new materials, produce construction and demolition waste, and generate 'embodied' GHG emissions from material production and construction activities. Evolution of building stocks can reduce energy-related emissions, as newer buildings replace older, less efficient buildings. However, embodied emissions are growing more important as buildings become more efficient and as the energy supply becomes less carbon intensive (Röck *et al.* 2020). The need to reduce embodied emissions becomes clearer when considering the limited remaining timeframe and carbon budgets for keeping climate change within 1.5–2.0°C warming. Building stock models are widely used to estimate building and material stocks and flows (Augiseau & Barles 2017; Lanau *et al.* 2019), energy and GHG emissions from building energy use (Langevin *et al.* 2020), and, in limited cases, GHG emissions from both building construction and energy use (Pauliuk *et al.* 2021; Pauliuk & Heeren 2020). The role of vacancies, and their influence on building construction, demolition, and material flows, is beginning to receive more attention in building stock models, particularly in regions with declining population and growing vacancy rates (Deilmann *et al.* 2009; Wuyts *et al.* 2020). Areas with high vacancy rates tend to have lower demand for new construction (Volk *et al.* 2019), while areas with low vacancy rates have higher construction demand (Zabel 2016). Improved modeling of construction and demolition considering local population growth and vacancy rates can facilitate more reliable construction and demolition material flow estimates at local levels (Schiller *et al.* 2017b), where reuse of bulky materials is more feasible.

This paper describes the development and application of a housing stock model for 3108 US counties (excluding counties in Alaska and Hawaii) and projects the evolution of the US housing stock by county over the period 2020–60. Dynamic, county-specific vacancy rates are incorporated in the model, and historical survey data are used to estimate region- and house type-specific 'natural vacancy rates.' Drawing on observed and natural vacancy rates in each timestep, novel approaches are applied to modeling stock additions and losses. The geographic resolution of US counties enables the estimation of housing stock evolution and material flows at a local level. Model results can thus demonstrate the potential (or lack thereof) for local circular reuse of construction materials. Housing stock and material flows, GHG emissions associated with new construction, and the progression of residential floor space per person are illustrated for six scenarios. The scenarios investigate the material demand and embodied GHG implications of different strategies with potential to reduce energy and embodied emissions in US housing.

2. REPRESENTATION OF VACANCY IN HOUSING STOCK MODELS

Research on housing markets in economics has yielded support for the existence of natural vacancy rates, which can generally be understood as the result of a housing search process by households with varying preferences within a heterogenous housing stock, and can vary by region (Rosen & Smith 1983; Wheaton 1990; Zabel 2016). Hwang & Quigley (2006), the first to include vacancies as an input to economic housing supply models, showed that lower vacancy rates are likely to persist in more heavily regulated housing markets. Zabel (2016) specified a model to estimate changes in housing supply based, in part, on local vacancy rates, and found that vacancy above the natural rate has a downward effect on new housing construction, while vacancy below the natural rate has an upward effect on new construction. These studies provide some explanations for non-zero vacancy rates in housing markets, building on the understanding of vacancy arising from a search process by mobile populations. They also indicate relationships between regulations, vacancy rates, and housing supply. Unlike dynamic stock models produced for material flow analyses (MFAs), however (Lanau *et al.* 2019), these economic models focus only on housing supply and do not disaggregate net stock growth into additions and losses.

In dynamic building stock models used in industrial ecology and MFA, explicit consideration of vacancy rates is an emerging practice. Disregarding vacancies can lead to infeasible negative inflows in cases of negative stock growth (due to population decline) (Deetman *et al.* 2020). This is largely because housing demolition does not respond to population decline in the same way that construction responds to population growth (Schiller *et al.* 2017a). Vásquez *et al.* (2016) address this issue by subtracting vacant floor area arising from declines in population from their estimates of in-use stock, but they do not account for what they call 'market vacancies.' Some models do incorporate explicit consideration of non-static vacancy rates. Deilmann *et al.* (2009) generated scenarios describing housing stock evolution in eastern and western Germany to 2050, highlighting the increase in vacancies that would accompany population decline, unless loss rates also increased. Roca-Puigròs *et al.* (2020) use three occupancy states (daily use, temporary use, and vacant stock) in their description of the Swiss housing stock, although vacancy rates did not change over time, or play a role in determining stock in- or outflows. Schiller *et al.* (2017a) estimate a maximum vacancy threshold to inform their calculation of residential demolition in Germany. Volk *et al.* (2019) use vacancy rates for multifamily buildings to approximate vacancy rates for residential and non-residential buildings in the German state of Baden-Württemberg, and model vacancy increases in response to reduced demand for new floor area, as well as reduced replacement of demolished buildings in regions with higher vacancy. These studies exemplify the evolving treatment of vacancy in building stock models. A prevailing approach to incorporating vacancy in such models has not yet emerged.

3. DATA AND METHODS

For this study, a bottom-up housing stock model is developed for US counties, classifying housing stocks by type (single-family, multifamily, manufactured housing; manufactured housing is a form of single-family, but has very different lifespan, vacancy rate, and material intensity characteristics), by construction cohort, and by vacancy status (occupied/vacant). The principal data sources used for model development are longitudinal datasets spanning the period 1985–2017, indicating the movement of housing units in and out of the housing stock (US Census Bureau 2017b), and the corresponding American Housing Survey (AHS) microdata (US Census Bureau 2020a). 'Components of inventory change' reports based on these data describe how a substantial portion of housing units move in and out of the stock from processes other than new construction and demolition (Eggers & Moumen 2016, 2020). In addition to demolition and disaster, housing stock losses also arise from houses changing to non-residential uses, becoming damaged or unfit for habitation, or from (mobile) manufactured homes moving out from the site where they were last surveyed. In addition to new construction, housing stock additions also occur from conversions from non-residential to residential use, recovery from temporary losses (including previously uninhabitable buildings returning to the housing stock), and manufactured homes moving into new sites. In these surveys and reports, a housing unit is only considered to be part of the total (occupied plus vacant) housing stock if it is physically fit for habitation, and available for residential use, *i.e.* not in use for a non-residential purpose.

Figure 1 shows a schematic diagram of the model inputs and outputs; *Table 1* details the variables and superscripts used in the equations that follow. The housing stock model is defined in equations (1) to (6) and the accompanying text. For further detail on the results processing, see **Section S5** and **Figure S11** in the supplemental data online.

The starting point for the model is the calculation of the occupied stock *S* (measured in housing units) of each house type in every county for each model year, based on county resident population *P*, county population share by house type $P_\%$, and average household size *HS* by house type (equation 1) (see *Table 1* for definitions of each variable and subscript):

$$S^{t,k,v=0,y} = P^{k,y} \times P_\%^{t,k,y} / HS^{t,k,y} \tag{1}$$

Population projections for US counties were generated using a blended cohort-change differences and cohort-change ratios model (Hauer 2019) for five shared socioeconomic pathway (SSP) scenarios (O'Neill *et al.* 2017). This study adapts Hauer's (2019) SSP2 ('middle of the road') county
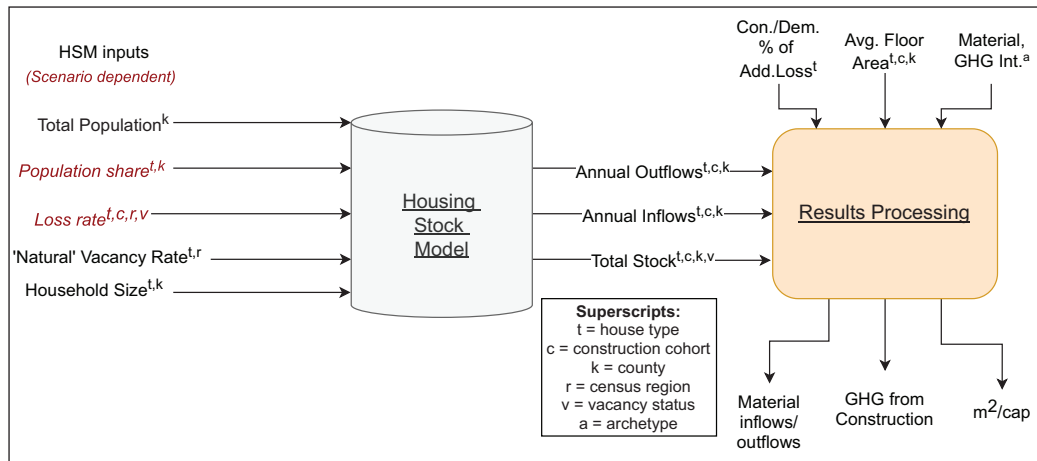
Figure 1: Schematic of inputs and outputs from the housing stock model.

Note: Con. = construction; Dem. = demolition; Add. = additions; Loss = losses. Int. = intensity, referring to material per unit of floor area (kg/m^2), greenhouse gas (GHG) per mass material (kgCO$_{2e}$/kg), and the resulting GHG per unit floor area (kgCO$_{2e}$/m^2). For a description of the results processing, see **Figure S11** in the supplemental data online.

SYMBOL	SUMMARY	UNIT OF MEASUREMENT/SUPERSCRIPT DETAIL
S	Housing stock	Number of housing units
P	Population	Persons
$P_\%$	Population share	(%)
HS	Household size	Persons/housing unit
L	Losses from stock	Housing units/year
LR	Loss rate	Lost housing units/total housing units
A_{+OSG}	Additions to the stock with positive OSG	Housing units/year
A_{-OSG}	Additions to the stock with negative OSG	Housing units/year
AR	Additions rate	Added housing units/total housing units
TSG	Total stock growth	Total housing units/year
OSG	Occupied stock growth	Occupied housing units/year
GF	Growth factor determining the ratio of TSG to vacancy-adjusted OSG	[ ]
VF	Vacancy factor (total stock/occupied stock)	[ ]
V	Vacancy rate (vacant stock/total stock)	[ ]
t	Superscript for house type	Three types (single/multi-family, manufactured home)
c	Superscript for house construction cohort	Ten cohorts
k	Superscript for US county	3108 counties
v	Superscript for house vacancy status	Two levels: 0 = occupied, 1 = vacant
r	Superscript for US Census region	Nine regions
y	Superscript for model year	Range covered: 2020–60

Table 1 Housing stock model variables and superscripts.

population projection to 2060, scaled first to the US Census Bureau mid-range national population projection (US Census Bureau 2017a) (see **Figure S1** in the supplemental data online) and again to the actual US resident population on 1 July 2020 (US Census Bureau 2020c), to bring the projections in line with recent US national population levels and projections. Estimates of future changes in household size (see **Figure S2** in the supplemental data online) are based on data from McCue (2018), and the same proportional reduction in household size is applied to all house types, while maintaining the initial differences in household size observed in different counties and house types. Initial estimates of household size and population share by house type in each county are derived from one- and five-year population and occupied housing unit estimates for 2019 from the American Community Survey's (ACS) tables B25033 and B25127 (US Census Bureau 2021). This estimation is elaborated further in **Section S1.1** in the supplemental data online.

In the second model step, losses are calculated from the housing stock based on annual loss rates, summarized in **Table S1** in the supplemental data online. Loss rates for each age cohort are calculated for each year based on the share of age ranges that exist in each age cohort. For example, in 2025, some of the houses built between 2000 and 2009 will be in the 0–19-year age range, while others will be in the 20–59-year age range, and so the loss rate for these houses will be a weighted average of loss rates for these two age ranges. Total housing losses (L) are then calculated as the product of total stock (S) by type, cohort, county, and vacancy, and corresponding loss rates (LR) (equation 2):

$$L^{t,c,k,v,y} = S^{t,c,k,v,y} \times LR^{t,c,r,v,y} \tag{2}$$

By adding an age-related dependency to loss rates, the modeling of decay of existing buildings combines the 'lifetime' and 'leaching' approaches described by Roca-Puigròs *et al.* (2020). The introduction of vacancy-dependent loss rates is a novelty of this model and motivated by the large differences in loss rates observed for occupied and vacant units. Vacant units are much more likely to leave the stock than comparable occupied units (see **Table S1** in the supplemental data online).

Next, additions to the stock are calculated with separate approaches employed depending on whether occupied stock growth (OSG) in a model year is positive or negative. Positive and negative OSG generally correspond to positive and negative population growth, but reductions in household size can also generate a positive OSG even in the case of zero or marginally negative population growth. In most housing stock models, it is assumed that there will be no new additions to the stock if the occupied stock does not grow. The authors' reading of AHS data suggests that this is not necessarily the case. At national and census region levels, positive additions to the stock occur even in times of negative OSG (see **Figure S4** in the supplemental data online). This can be explained by some demand for new housing existing within a region, even if the occupied stock in the region as a whole declines. A linear model (see **Table S4** in the supplemental data online) is used to estimate the addition rate ($AR \geq 0$) conditional on the OSG rate in cases of negative OSG. This estimate of AR is then multiplied by the total stock to calculate additions to the stock in cases of negative OSG, A_{-OSG} (equation 3):

$$A_{-OSG}{}^{t,k,y} = \widehat{AR^{t,r}} \times S^{t,k,y} \tag{3}$$

For cases of positive OSG, annual additions to the stock, A_{+OSG}, are calculated as the sum of total stock growth (TSG) and losses (L) (equation 4). TSG equals the product of OSG, a 'natural' vacancy factor (VF_n), and an estimated stock growth factor (GF), which defines the ratio of actual TSG to vacancy adjusted OSG (see equation S1 in the supplemental data online).

$$A_{+OSG}{}^{t,k,y} = TSG^{t,k,y} + L^{t,k,y} = (\widehat{GF}^{t,k,y} \times VF_n^{t,r} \times OSG^{t,k,y}) + \sum_{c,v} L^{t,c,k,v,y} \tag{4}$$

The natural vacancy factor VF_n is defined as the total stock divided by the occupied stock when vacancy is at the natural level. VF_n is equivalent to $(1 - V_n)^{-1}$, where V_n is the natural vacancy rate. GF can fluctuate, increasing or decreasing the level of stock growth (and consequently additions to the stock) in order to move the stock towards the natural vacancy rate. For example, if vacancy rates are below the natural rate, $GF > 1$, which will increase additions to the stock and cause the vacancy rate to increase. If vacancy rates are above the natural rate, $GF < 1$, reducing additions to the stock and causing the vacancy rate to decrease. A linear model is specified to estimate GF as a linear function of changes in the vacancy factor dVF (see **Figures S5–S7** in the supplemental data online) based on historical AHS data (US Census Bureau 2017b, 2020a). The value of GF is estimated conditional on the change in vacancy factor dVF, assuming that dVF equals half the difference between the actual vacancy factor and the natural vacancy factor in a given year, *i.e.*:

$$dVF^y = 0.5 * \left(VF_n - VF^y\right).$$

This specification reflects the assumption that in growing stocks, vacancy factors (and vacancy rates) will tend towards the exogenously determined natural level, with the factor 0.5 preventing the gap between actual and natural VF from being closed too quickly. If the housing stock is already at the natural vacancy rate, $GF = 1$ and TSG is simply the product of VF and OSG.

Natural vacancy rates are estimated using the mean vacancy rates for each house type and census region calculated from AHS data for the period 1985–2019. National vacancy rates average approximately 10%, 15%, and 20% for single-family, multifamily, and manufactured housing, respectively, with some variation around these levels for different census regions (see **Figure S8** in the supplemental data online). To describe vacancies in the housing stock in 2020, vacancy rates are calculated by type, cohort, and county using data on occupied and total housing stocks from ACS tables DP04 and B25127 (US Census Bureau 2021). The total stock by type for the beginning of year $y + 1$ is calculated based on the initial stock, additions, and losses in year y (equation 5), and vacancy factors are then calculated as total stock divided by occupied stock (equation 6):

$$S^{t,k,y+1} = S^{t,k,y} + A^{t,k,y} - L^{t,k,y} \tag{5}$$

$$VF^{t,y+1} = S^{t,k,y+1}/S^{t,k,v=0,y+1} \tag{6}$$

In order to calculate material flows associated with additions and losses to the stock, first the additions and losses are converted into new construction and demolition. The portion of additions to the stock coming from sources other than new construction varies by region and type, but additions from new construction tend to be around 85% of total additions (see **Table S2** in the supplemental data online). For demolition, it is assumed that on average 35%, 20%, and 45% of single-family, multifamily, and manufactured housing losses from stock are due to demolition or disaster (see **Table S3** in the supplemental data online). The resulting estimates of material in- and outflows are very sensitive to the conversion of additions to new construction, and losses to demolition, respectively. The percentages of losses from demolition that are adopted here are slightly higher than historical rates (see **Table S3** online), because it is assumed that many of the houses that leave the stock for reasons other than demolition will likely be demolished in subsequent years, and therefore actual demolitions in a given year will include demolition of some 'hibernating stock' (houses that left the in-use stock in previous years, which are not picked up by AHS statistics). Some remaining houses that leave the stock will not be demolished while materials are still recoverable, leading to 'dissipative flows' of building materials which cannot be recovered (Jelinski *et al.* 1992).

Estimates of average floor area per house type, cohort, and county are based on floor area characteristics by core-based statistical areas (CBSA) from the AHS 2017 survey, as incorporated in the ResStock housing characteristics database (NREL 2020). Details for estimating floor area characteristics at county resolution are given in **Section S2** in the supplemental data online. Housing characteristics for Hawaii and Alaska are excluded from the ResStock database, and so the model also excludes these states, which together represent 0.6% of the US housing stock. In all cases, references to floor area describe 'useful floor area,' which excludes basements and garages. Total occupied floor area is calculated by multiplying the number of occupied housing units per county by the average floor area per house (see **Figure S11** in the supplemental data online). Combining the occupied floor area data with population estimates, the evolution of floor area per person (m^2/cap) per county and house type is then calculated. Floor area and population data can then be aggregated to calculate the floor area per person for all house types and/or for larger geographic units. Calculating floor area per person as a model output contrasts with the approach in most housing stock models, where floor area per person is an exogenously assumed model input, reflecting service level (Müller 2006; Pauliuk *et al.* 2021; Roca-Puigròs *et al.* 2020). The approach taken here facilitates the identification of stock characteristics and dynamics that will influence the future growth of floor area per person, and the identification of strategies than can be pursued to constrain this growth. Average floor area per house type, cohort, and county are also used to convert construction and demolition flows from housing units into floor area in- and outflows (see **Figure S11** online).

The Athena Impact Estimator (Athena Sustainable Materials Institute 2020) is used to generate material intensities for 51 housing archetypes (described in **Section S3** in the supplemental data online), and these are then used to estimate weighted-average material intensities by house type and county for 48 construction materials. To calculate material-related GHG intensities, 29 material categories are then defined for which GHG emissions/kg of material production are

obtained. Material GHG intensities come from a variety of sources including environmental product declarations and life-cycle assessment databases (Jones 2019; Wernet *et al.* 2016). Intensities are based on the most recent and US-representative sources where possible. GHG emissions from construction site transport and energy use are incorporated based on archetype-specific estimates from Athena, scaled to be more consistent with literature estimates (see *Table S6* in the supplemental data online). Archetype characteristics are summarized in *Table S5* in the supplemental data online; the GHG intensity from all materials and construction activities per floor area is shown in *Figures S9* and *S10* in the supplemental data online. Avoiding basement foundations, building multi-storey (for a given floor area), and building without a garage are some options that exist for reducing GHG emissions from new single-family construction.

Six scenarios of housing stock evolution are generated along dimensions of population share by house type, housing stock loss rates, and average size of new housing (*Table 2*). The scenarios reflect housing stock strategies that may be adopted to reduce direct energy demand, and energy and embodied emissions. The effects of these scenarios on energy consumption and emissions are the focus of future research. This paper demonstrates housing and material flows, and related emissions, for each scenario at a county and national level. In a *Baseline* scenario, population share by house type is assumed to remain constant throughout the projection period. In a *High Turnover* scenario, the loss rates (see *Table S1* in the supplemental data online) are increased by a factor of 1.5, which is comparable to reducing the average lifetime for all housing by one-third. In cases of positive OSG, this will directly produce higher stock additions, as described in equation (4). For negative OSG, the factor of 1.5 is also applied to the additions estimated in equation (3). In a *High Multifamily* scenario, the share of the population living in multifamily is increased by 0.25 percentage points (pp)/year in counties where the population grows by at least 5% over 20 years between 2020–40 and 2040–60. The *High Turnover & High Multifamily* scenario simply combines the loss rate and population share assumptions of scenarios 2 and 3. In a *Reduced Floor Area* scenario, the floor area distributions are redefined so that any new house >279 m² (3000 square feet) is instead in the range of 186–278 m² (2000–2999 square feet) (*cf.* *Figure S15* in the supplemental data online). To put this scenario in the context of recent trends, between 25% and 30% of new single-family houses built in the 2010s were ≥279 m² (US Census Bureau 2020b). In order to fit with scenarios in which residential floor area consumption converges to a range of 30–40 m²/cap (Grubler *et al.* 2018; Hertwich *et al.* 2020), a 279 m² house would require seven to nine inhabitants. In 2019, houses of ≥279 m² had on average 3.06 occupants (US Census Bureau 2020a). The *High Multifamily, Reduced Floor Area* scenario combines the population share and floor area distribution assumptions of scenarios 3 and 5. With the exception of the *Reduced Floor Area* scenarios (5 and 6), floor area characteristics for new housing in future cohorts are assumed to remain the same as housing built in the 2010s (see *Figures S14* and *S15* in the supplemental data online).

Table 2 Summary description for six housing stock scenarios. Multifamily population increases apply only to counties where population growth > 5% over 20 years for the periods 2020–40 and 2040–60.

Note: FA = floor area; pp = percentage points.

SCENARIO	1 BASELINE	2 HIGH TURNOVER	3 HIGH MULTIFAMILY	4 HIGH TURNOVER AND MULTIFAMILY	5 REDUCED FA	6 HIGH MULTIFAMILY, REDUCED FA
Loss rate	Historical rates by region	1.5× Historical rates by region	Historical rates by region	1.5× Historical rates by region	Historical rates by region	Historical rates by region
Multifamily population	2020 share by county	2020 share by county	Increase 0.25 pp/year	Increase 0.25 pp/year	2020 share by county	Increase 0.25 pp/year
Floor area distribution, new homes	Same as 2010s	Same as 2010s	Same as 2010s	Same as 2010s	No homes > 279 m²	No homes > 279 m²

4. RESULTS

4.1 AGGREGATED NATIONAL RESULTS

Figure 2 shows annual additions and losses to the stock, aggregated to the national level, from 2020 to 2060 for the six housing stock scenarios. In all scenarios, additions to the stock are higher

than losses, reflecting continual stock growth. In the *High Turnover* scenarios, there are much higher levels of stock losses and additions. In the *High Multifamily* scenarios, multifamily inflows are substantially higher than in the *Baseline*, and become higher than single-family additions in the late 2020s/early 2030s. Because these figures depict flows of housing units and not floor area, scenarios 1 and 5 are identical, as are scenarios 3 and 6.
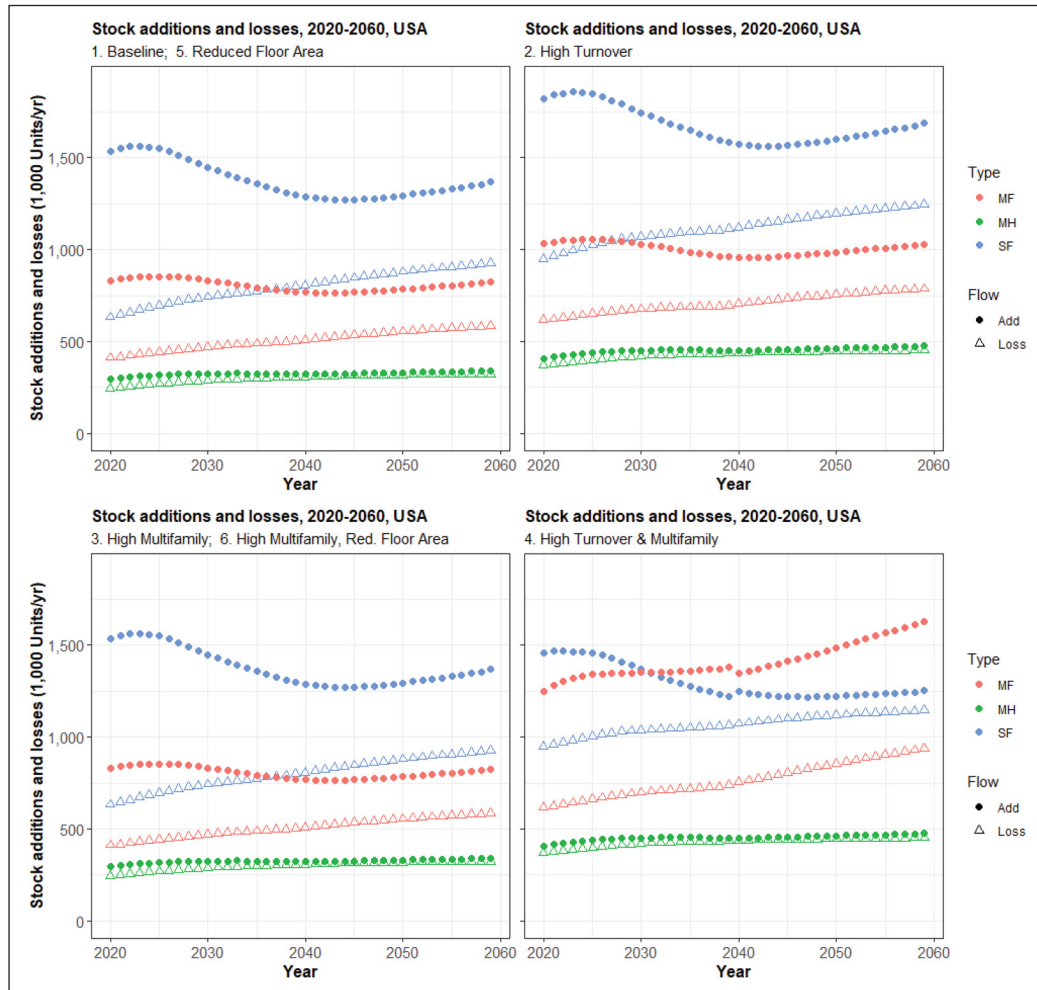
Figure 2: Inflows (additions) and outflows (losses) from stock for three house types for each housing stock scenario.

Figure 3 compares the growth of national single- and multifamily stocks in scenarios 1 and 4. From a 2020 level of 94 million units, the stock of single-family houses grows to 103 million units by 2060 in scenario 4, compared with 117 million units in the baseline scenario 1. The multifamily stock grows from 38 million units in 2020 to 50 million (scenario 1) or 64 million (scenario 4) units by 2060. With higher stock turnover, the existing stock declines slightly faster. The pre-1960 housing declines from 27.3% of the total housing stock in 2020 to 14.4% in 2060 in scenarios 1, 3, 5, and 6, or 11.9% in scenarios 2 and 4. These relatively small differences in decline of older housing demonstrate that even with a considerable increase in demolition rates, more than 10% of the housing stock in 2060 will be over 100 years old.

Figure 4 shows the implications of the housing stock scenarios for the evolution of national occupied floor area per person (m²/cap). In the Baseline scenario, steady growth occurs from 60.2 m²/cap in 2020 to 69.2 m²/cap by 2060. Although declines in average household size play some role, this growth in m²/cap is primarily because housing built from 2020 onwards is much larger on average than housing that leaves the stock, which is mostly from the early and mid-1900s (see *Figure S14* in the supplemental data online). Speeding up the turnover rate in scenario 2 accelerates this growth, and floor space per person reaches 70.7 m²/cap by 2060. Due to lower floor area per person in multifamily housing, increasing the multifamily share in scenario 3 attenuates the growth in floor area per person, which grows to 64.4 m²/cap by 2060. The *Reduced Floor Area* scenario shows floor area per person stabilizing at 62.0 m²/cap from 2040 onwards, while the
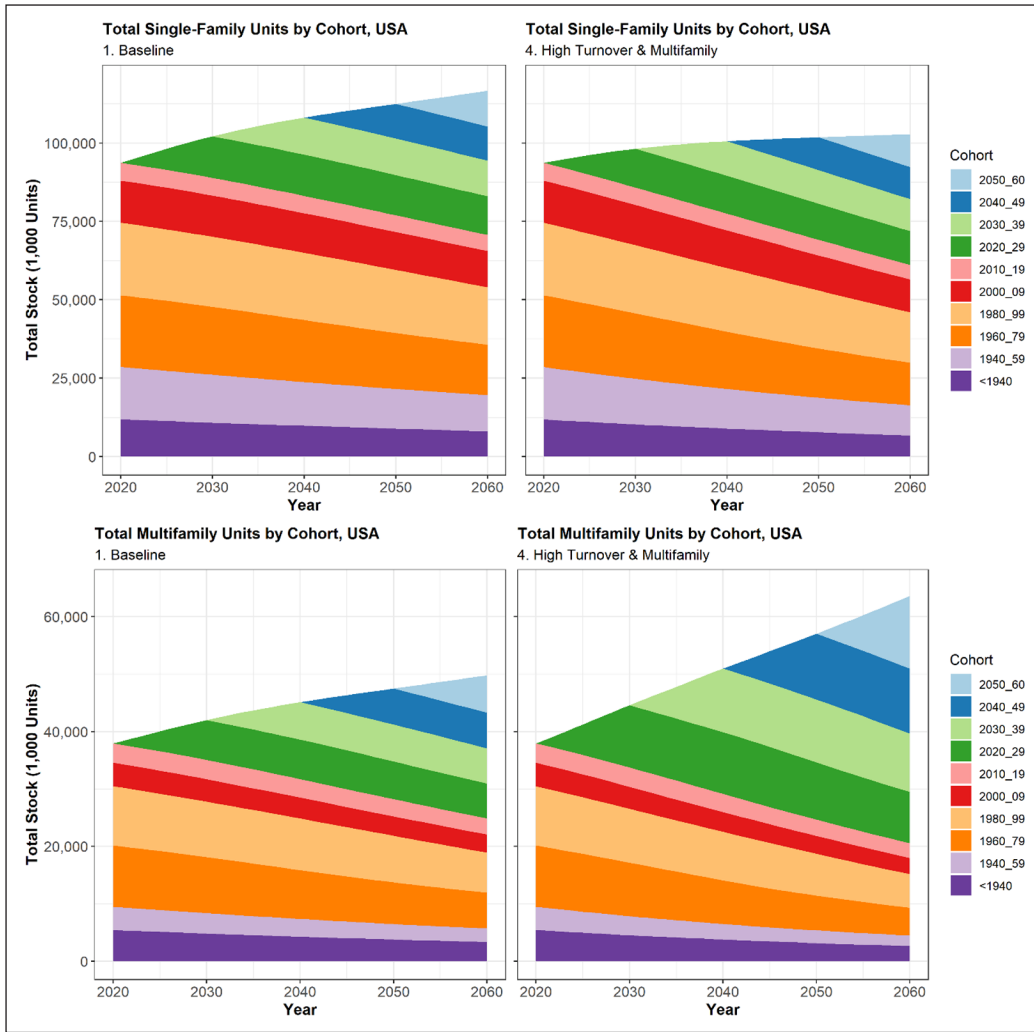
Figure 3: Evolution of single- and multifamily housing stocks by construction cohort for two scenarios.
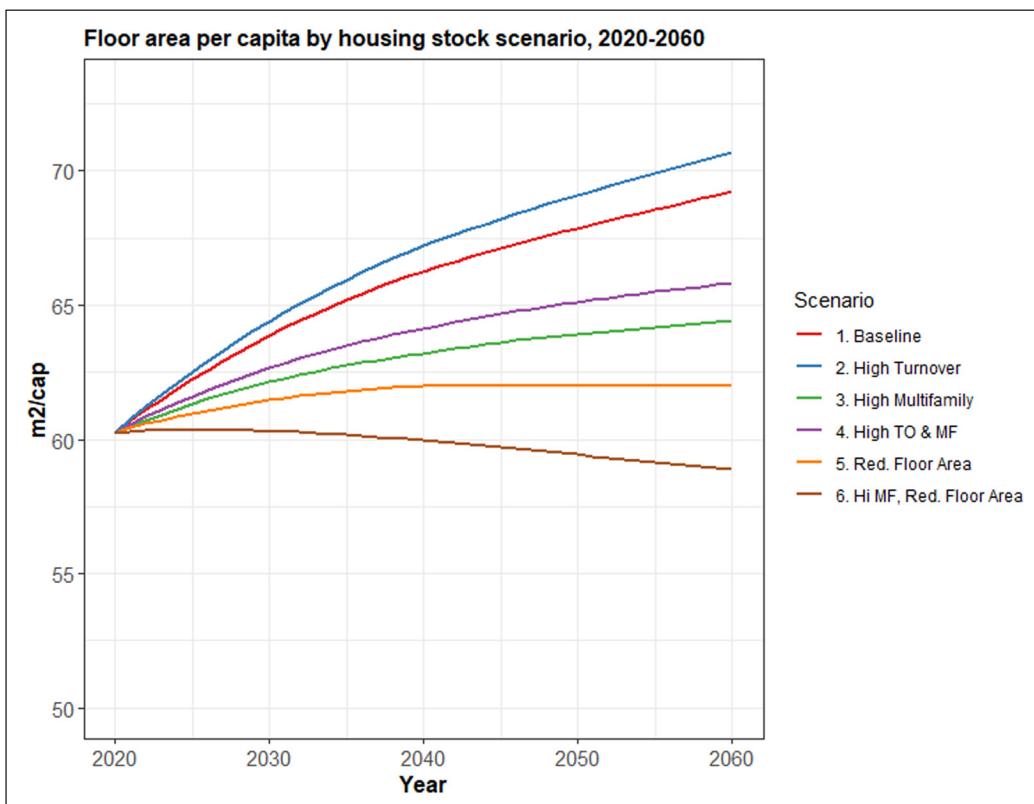

Figure 4: Occupied floor area per person in each housing stock scenario.

lowest trajectory is achieved by combining high multifamily and reduced floor area (scenario 6), which reduces floor area per person to 58.9 m²/cap by 2060. The limited reduction of floor area per person achieved in only one scenario demonstrates the difficulty of reducing m²/cap only through altering the characteristics of new construction. Floor area consumption in the US is already high by international standards (Ellsworth-Krebs 2019). Floor area consumptions in 2020 and 2050 are shown for all counties in **Figure S24** in the supplemental data online, illustrating the geographic variation in m²/cap.

Figure 5 shows national total floor area inflows and outflow, and cumulative GHG emissions from material production and residential construction activities in each scenario. In the *High Turnover* scenarios (2 and 4), floor area inflows and related emissions are larger due to the higher demolition and construction activity. Cumulative 2020–60 emissions from new construction are higher in *High Turnover* scenario 2 than *Baseline* scenario 1 by 0.69 Gt CO_{2e}, which is 77% of 2020 emissions from residential energy use (EIA 2021). Although more new housing units would need to be built in the *High Multifamily* scenarios (due to lower household size and higher vacancy rates in multifamily homes), floor area inflows and emissions from new construction are lower if the multifamily share increases, due to the much lower average floor area per unit. Cumulative 2020–60 emissions from new construction are lower in *High Multifamily* scenario 3 than *Baseline* scenario 1 by 0.33 Gt CO_{2e}. Further reductions in emissions from new construction occur in the *Reduced Floor Area* scenario, where emissions are 0.58 Gt CO_{2e} lower than in the *Baseline* scenario. The lowest emissions occur in the *High Multifamily, Reduced Floor Area* scenario, in which emissions are 0.77 Gt CO_{2e} lower than the *Baseline*. **Figure S16** in the supplemental data online breaks down emissions by aggregate material and construction categories, demonstrating the prominence of fiberglass-based products (including roofing, window frames, and doors), concrete and cement, steel, and transport and site energy.
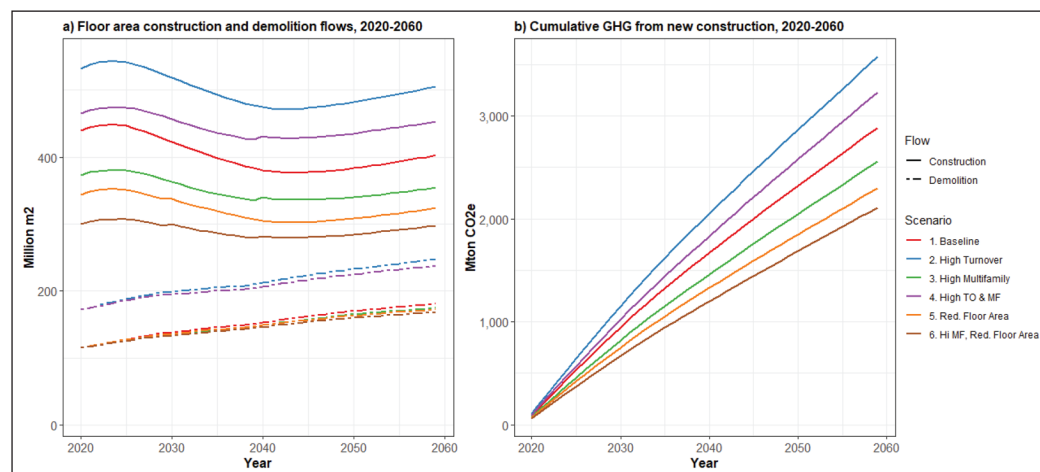

Figure 5: (a) Floor area in- and outflows from construction and demolition; and (b) cumulative greenhouse gas (GHG) emissions from new residential construction for five housing stock scenarios.

4.2 SELECTED COUNTY RESULTS

Next, stock model results are compared for four counties, selected to demonstrate the granular nature of the model output, and illustrate results for counties with contrasting population and housing stock growth trajectories (see **Figure S3** in the supplemental data online). Harris County, Texas (home to Houston city), is a county with high projected population growth. Providence, Rhode Island, is a county with low projected population growth. San Juan County, New Mexico, is a county expected to see major population decline, and Marquette County, Michigan, is projected to have modest population decline.

Figure 6 shows the projected total stock of multifamily housing for each of these counties for the *Baseline* scenario. In Harris County, strong population growth translates into large increases in housing from the new cohorts. In Providence County, modest additions of multifamily housing occur in the new cohorts (much more than additions in the 2000s and 2010s, but still less than additions in the 20th-century cohorts). Overall, the total stock grows only slightly, as

new construction occurs mostly to replace losses from the existing stock. Providence is notable for having a much larger share of pre-1960 housing than the other counties featured, which is characteristic of early-developed urban counties in the US, particularly those in the Northeast and Midwest. In San Juan, population decline is so great that no construction of new multifamily (or single-family) housing is estimated between 2020 and 2060. Despite the steady decline of the housing stock, population decline is more rapid, and so the vacancy rates steadily increase (see *Figure S13* in the supplemental data online). Marquette County shows a modest decline in housing stock, starting in 2030 when the population starts to decline. However, there are still non-negligible flows of new construction in future cohorts to make up for losses from the existing stock (and to accommodate declines in household size). Regarding the relation of housing stock growth and vacancy rates (see *Figure S13* online), in fast-growing counties such as Houston, vacancy rates approach the natural rate relatively quickly, and remain steady once the natural rate has been approximated. In slow-growing counties, vacancy rates move toward the natural rate much more slowly. As the formulation for stock additions under a negative OSG has no basis in natural vacancy rates (equation 3), there is no mechanism by which natural vacancy rates are achieved in declining counties. To address this, loss and addition rates are adjusted to curb excessively high or low vacancy rates (*cf.* *Section S1.2* in the supplemental data online). However, in some cases, even with zero construction, vacancy rates can still increase, as exemplified by San Juan. The locations of these four counties are shown in *Figure 8*.
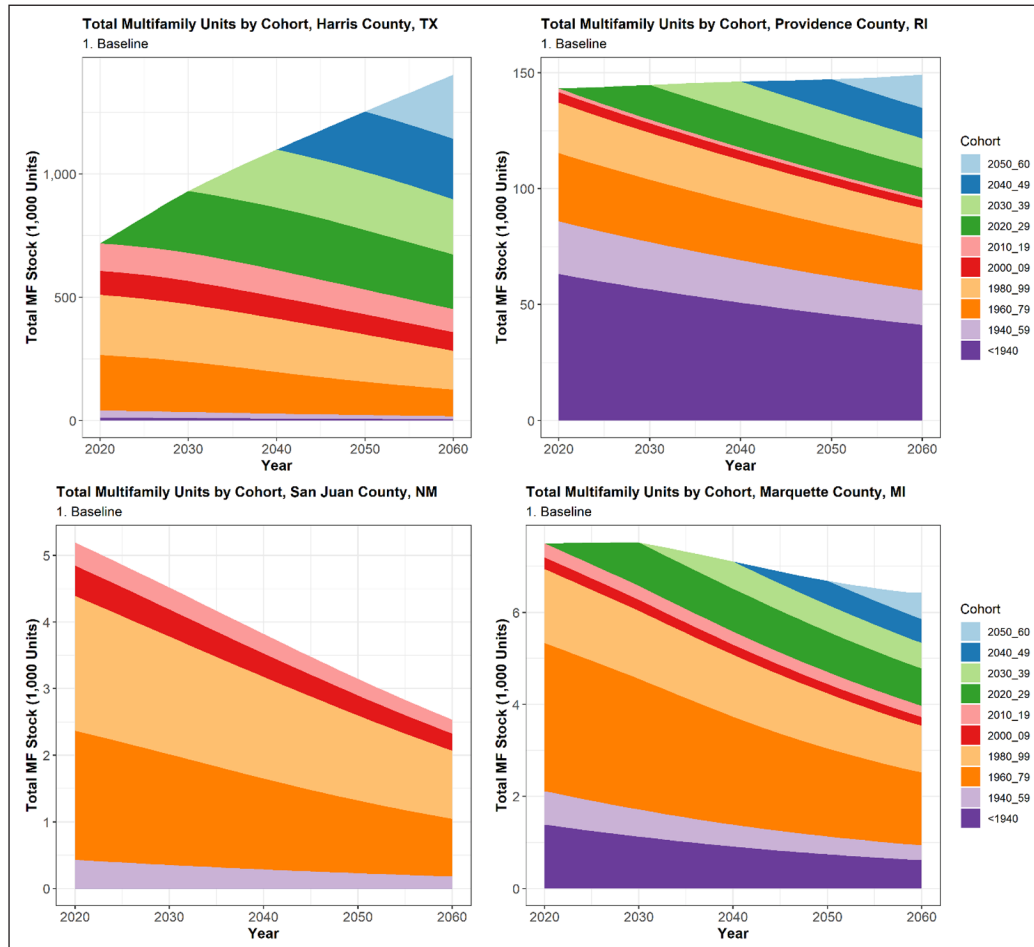

Figure 6: Multifamily stock evolution by construction cohort for selected counties.

Figure 7 demonstrates in- and outflows of concrete associated with construction and demolition for the four selected counties. Concrete is by far the most massive material in most archetypes, and the most prominent in overall material flows (see *Figure S17* in the supplemental data online). Even in most wood-framed homes (excluding those with pier and beam foundations), concrete is the main material component (see the 'Full_arch_intensities.csv' file in the online github repository, mentioned below in the Supplemental Data section), due to the large mass of concrete used in

the foundations. Of these four counties, only Harris County has sufficient population growth to activate the increase in multifamily population share in *High Multifamily* scenarios. For the other three counties, population shares by house type do not change in *High Multifamily* scenarios, and there is no difference in results between scenarios 1 and 3, 2 and 4, or 5 and 6. In Harris County, there are higher material flows associated with *High Turnover* scenarios, and lower material flows associated with *High Multifamily* and *Reduced Floor Area* scenarios, consistent with national floor area flows (*Figure 5*). In Harris and Providence counties, material inflows are much larger than the material outflows. In the declining counties, material inflows may be smaller, similar, or larger than outflows. The *Reduced Floor Area* scenarios (5 and 6) require the smallest inflows of concrete.
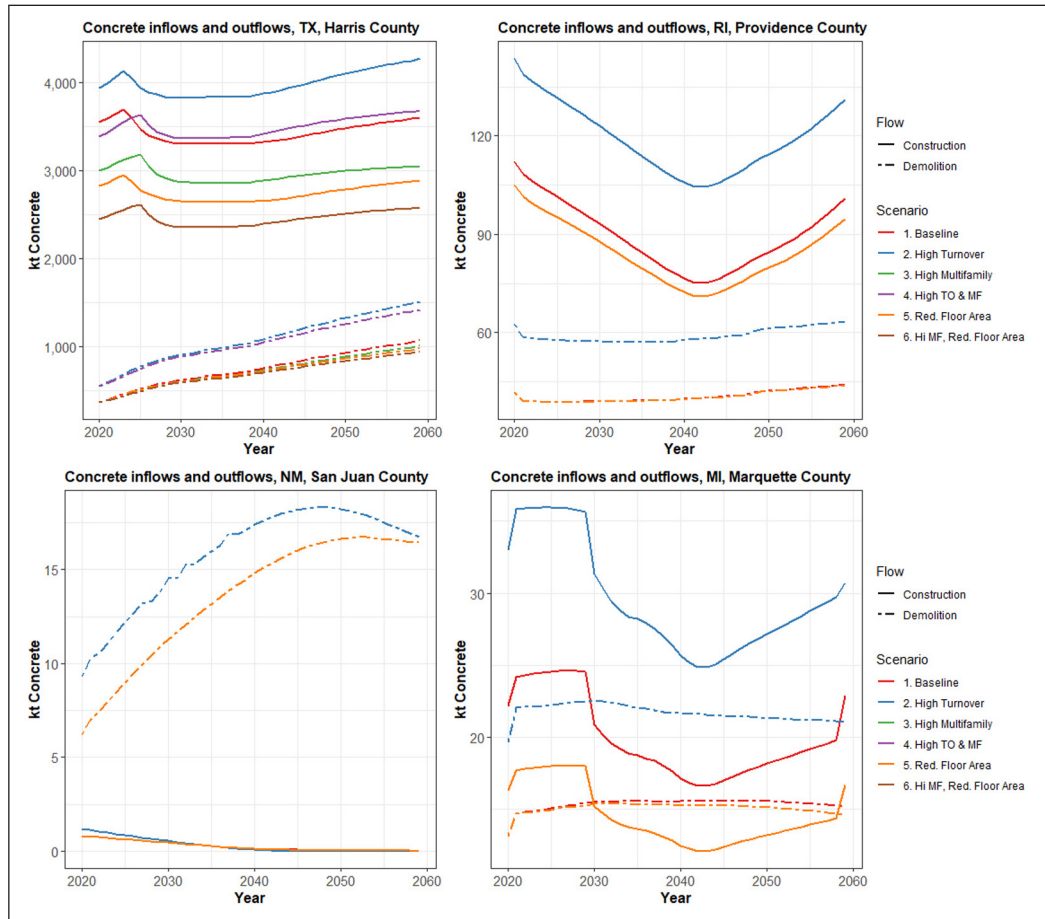

Figure 7: Concrete in- and outflows in selected counties for five housing stock scenarios. In Providence (Rhode Island), San Juan (New Mexico), and Marquette (Michigan) counties, population growth is not high enough to activate the growth of multifamily population shares in high multifamily scenarios, and thus results for scenarios 1 and 3, 2 and 4, and 5 and 6 are the same.

The comparison of material in- and outflows at the local level can be used to estimate potential for material reuse within a limited geographic area. *Figure 8* shows the ratio of demolition and construction-related concrete out- and inflows for all counties in 2020 and 2040. Similar figures for concrete and other materials for more years are shown in *Figures S18–S20* in the supplemental data online. A substantial number of (brightly colored) counties have outflows that are higher than inflows in 2020. The prevalence of such counties grows considerably between 2020 and 2040. The darker colored counties are generally higher population growth counties with positive stock growth. In such locations new construction is high enough to create opportunities for material reuse in new construction, but the reuse of waste materials will be far from sufficient to supply the total materials requirements for new construction. In bright colored counties, a larger portion of new construction could make use of materials sourced from demolition activities, but the overall demand for new construction is lower, decreasing the potential for material reuse in new construction. In the nation as a whole, the ratio of demolition to construction-related material flows grows from 0.25–0.35 (depending on the scenario) in 2020 to about 0.45–0.55 in 2060 (see *Figure S21* in the supplemental data online). The progression of overall vacancy rates 2020–50 is shown by county in *Figure S22* in the supplemental data online.
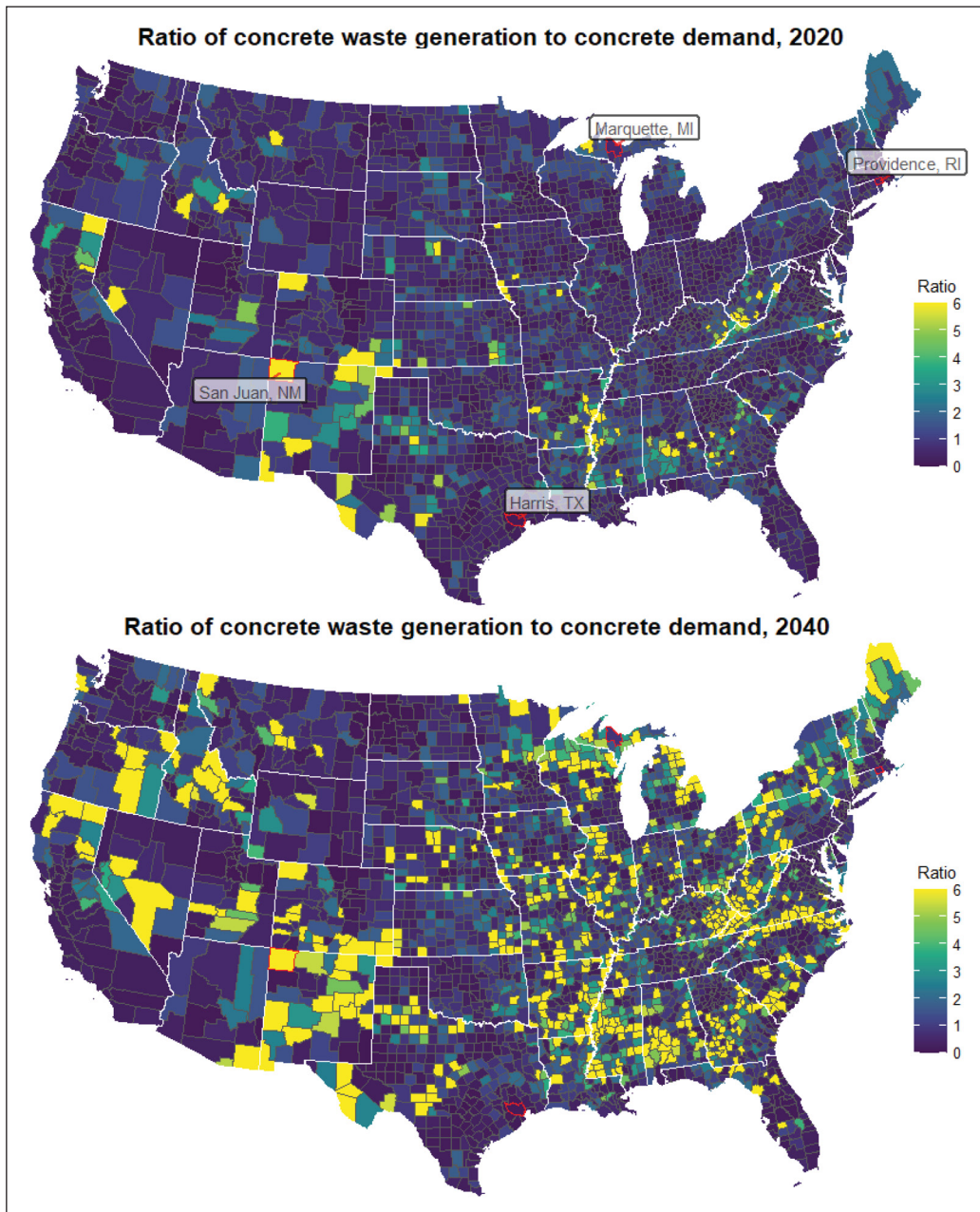
Figure 8: Ratio of concrete waste generation to demand for US counties, 2020 and 2040.

5. DISCUSSION

Given the long lifetime of housing in the US (most recently estimated as 130 years on average; Ianchenko *et al.* 2020), and the slowdown in stock turnover observed in some areas, due in part to local regulations (Reyna & Chester 2015), there may be an energy-efficiency-based rationale for increasing the rate at which new housing replaces old housing. The potential benefits of increased stock turnover for reducing total (embodied and energy-related) residential GHG emissions are, however, unclear. Because new houses tend to be much larger than older houses, housing stock growth and turnover causes floor area per person to increase steadily in most scenarios (*Figure 4*). This increase would be accelerated by higher turnover rates, reducing some of the energy efficiency benefits of newer housing (Viggers *et al.* 2017). Further, higher turnover clearly entails higher material flows and embodied emissions. Whether the energy and GHG reductions associated with more efficient newer housing would outweigh the floor area increases and additional embodied emissions is an important question which will be addressed in future research. The high turnover scenarios would produce a greater opportunity for material reuse, as the number of redundant vacant units (in excess of the natural vacancy rate) would be reduced (see *Figure S23* in the supplemental data online), and their materials would become available for potential

reuse. GHG benefits from material recycling or reuse are not assessed in this model, but increased recycling may reduce emissions from new construction. The potential for material reuse could be investigated at a local level by adopting a continuous-MFA approach, accounting for the recovery and processing losses and reuse potential for secondary materials (Schiller *et al.* 2017a). Emission reductions from circular reuse of materials are not guaranteed, and depend on many factors, including the ability to displace primary material production, local demand for reuse, and level of material transport required (Andersen *et al.* 2020; Zink & Geyer 2019).

Both increasing the share of multifamily population and reducing the size of new houses would reliably reduce emissions from new construction, and limit the growth in floor area per person, enabling further reductions in emissions from energy consumption. In the high multifamily scenarios, annual additions of multifamily housing become higher than additions from single-family around 2030. This would be a substantial departure from current trends, but may be feasible if momentum to remove restrictions (including single-family zoning, minimum lot sizes, height and density limits, and setback and parking requirements) (Gyourko *et al.* 2019) on multifamily and small single-family continues to grow. Several city and state governments across the US are considering or moving towards the removal of single-family zoning (Bliss 2021). In addition to removing land-use restrictions, reform of other policies which hinder multifamily development may also help to encourage smaller typologies in new construction. Federal tax and finance regulations currently encourage single- over multifamily development (Berrill *et al.* 2021), while local property taxes tend to be higher for rental housing (Goodman 2006), which is predominantly multifamily.

In reduced floor area scenarios, the average size of new single-family homes decreases from 258 to 192 m^2. Limiting the construction of very large, new single-family homes may be a different type of challenge than removing barriers to new multifamily and small single-family. Although many policy changes (dezoning, removal of lot size and density limits, *etc.*) that would permit more multifamily would also encourage smaller single-family (Gray & Furth 2019), there are other dynamics such as household preferences (Estiri 2014) and industry structure (Carlyle 2016) which are part of the explanation for the growth in size of new single-family homes. More research is needed to better understand the growth in size of new single-family homes, and identify strategies to reduce the average size of new housing (Cohen 2021). The results shown in *Figure 4* illuminate the difficulty of substantially reducing floor area per person by building smaller new housing alone. In scenario 6 with higher shares of multifamily housing and smaller single-family in new construction, there is a very slight reduction of floor area per person from 60.2 to 58.9 m^2/cap from 2020 to 2060. This is still far higher than the range of 30–40 m^2/cap used in scenarios aimed at limiting climate change to 1.5–2.0°C (Grubler *et al.* 2018; Pauliuk *et al.* 2021; van den Berg *et al.* 2021). Building smaller homes is necessary to limit the growth of m^2/cap, but by itself may at best achieve only minor reductions. More ambitious reductions of m^2/cap would require additional strategies such as increases in household size (Ivanova & Büchs 2020) or conversion of large single-family homes into multiple housing units (Garcia *et al.* 2020).

Developments in material stock and flow modeling have brought about increasing spatial resolution, particularly in studies that combine MFAs with geographic information system (GIS) data (Haberl *et al.* 2021; Yang *et al.* 2020). Although the spatial resolution of this housing stock model is lower than GIS-based studies, the geographical unit of US counties is still useful for comparing local-scale material in- and outflows and the potential for local material reuse without the need for long-distance transportation. The introduction of dynamic vacancy rates into housing stock models is a particularly important innovation. Incorporating vacancy rates that can change over time is an inescapable requirement for modeling building stock evolution in regions with low or negative population growth. This is best achieved at a subnational level in order to incorporate locally specific vacancy rates and population growth prospects (Deilmann *et al.* 2009; Volk *et al.* 2019). As most industrialized and post-industrial nations fit the low- and slowing population growth paradigm, and with declining fertility rates globally (Vollset *et al.* 2020), more explicit consideration of vacancy in housing stock models is increasingly important. The specification of housing stock in- and outflows with reference to locally observed and regional 'natural' vacancy

rates here represents a novel approach to housing stock modeling, and contributes to the emerging incorporation of vacancy in housing stock models.

The limitations of the model are now highlighted to identify areas that can be improved and extended. Although the archetype approach defines material intensities based on many different housing characteristics, age dependencies were not considered, so each archetype is assumed to have the same material intensity regardless of year of construction. For vacancy rates, historical average vacancy rates by house type and Census Division were assumed to represent natural vacancy rates. This simplifies matters and overlooks regional drivers of vacancy rates such as local regulations, economies and housing markets, land prices, *etc.* (Hwang & Quigley 2006). Defining vacancy rates, and other stock characteristics such as the prominence of multifamily and smaller housing, with reference to local restrictions (Gyourko *et al.* 2019) could shed light on the role of regulations and implications of future policy changes. The results of material in- and outflows are just a first step in assessing the potential for material recycling and reuse. Applying the continuous-MFA method would enable the estimation of the actual potential for material reuse and related GHG emission reductions. Finally, the results of the housing stock model are based on one scenario of population growth. Different national and localized population trajectories could produce quite different results. Current population trends in the US suggest that population growth in the coming decades may be less than the 'mid-range' census projection that was employed in this study.

6. CONCLUSIONS

A novel housing stock model is presented for US counties incorporating dynamic vacancy rates, with different scenarios of housing stock turnover rates and characteristics to 2060. As the growth of the population and housing stock slows, the ratio of demolition to construction material flows grows from 0.25–0.35 in 2020 (depending on the scenario) to 0.45–0.55 in 2060. Reducing the average size of new single-family housing and increasing the share of multifamily in new construction are two strategies that can reliably reduce material requirements and embodied emissions from housing stock growth. Both strategies would represent substantial departures from current trends, and would require policy changes to remove existing barriers and disincentives to multifamily and small single-family housing. Increasing stock turnover would accelerate the growth in floor area per person and increase emissions from residential construction.

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COMPETING INTERESTS

The authors have no competing interests to declare.

ETHICAL APPROVAL

Ethics approval was not required for this research

SUPPLEMENTAL DATA

Supplemental data for this article can be accessed at: *https://doi.org/10.5334/bc.126.s1*

Readers can also access the source data, modelling code (executed using the R software environment), and data outputs used and produced for this research at the following public repository: *https://github.com/peterberr/US_county_HSM*

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