Material flows and GHG emissions from housing stock evolution in US counties, 2020-2060

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Abstract

The evolution of housing stocks determines demand for construction materials and energy, and associated emissions of greenhouse gasses. The contribution of construction to building life cycle emissions is growing as buildings become more energy efficient and energy supply decarbonizes. In this paper we develop a housing stock model for United States counties, using dynamic vacancy rates which endogenously influence stock outflows and inflows. We project stocks of three house types and ten construction cohorts for all counties in the United States, for the period 2020-2060. We estimate inflows and outflows of construction materials, and greenhouse gas 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. Our 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 United States. 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 which 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. Policy makers can reduce residential sector emissions in the short and long term 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 construction and operation of buildings will play a key role in determining the feasibility of achieving ambitious climate change mitigation targets (Krausmann, Wiedenhofer, & Haberl, 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 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°C warming. Building stock models are widely used for estimating 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., 2020; Pauliuk & Heeren, 2020). The role of vacancies in building stock models, 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, Effenberger, & Banse, 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, Gruhler, & Ortlepp, 2017b), where reuse of bulky materials is more feasible.

In this paper, we describe the development and application of a housing stock model for 3,108 US counties (excluding counties in Alaska and Hawaii), and project the evolution of the US housing stock by county over the period 2020-2060. We incorporate dynamic, county-specific vacancy rates in our model, and using historical survey data we estimate region and house type-specific 'natural vacancy rates' which we assume housing stocks tend towards. Drawing on observed and natural vacancy rates in each timestep, we develop novel approaches to modeling stock additions and losses. The geographical resolution of US counties enables estimation of housing stock evolution and material flows at a local level. Model results can thus demonstrate potential (or lack thereof) for local circular re-use of construction materials. We illustrate housing stock and material flows, GHG emissions associated with new construction, and the progression of residential floor space per person 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 and 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 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 material flow analysis, 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, Gruhler, & Ortlepp, 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 occupancies states (daily use, temporary use, 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 inflows 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 lower 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 we develop a bottom-up housing stock model 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 1985-2017, indicating 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, and Table 1 details the variables and superscripts used in the equations that follow. The housing stock model is defined in Equations 1-6 and the accompanying text. Further detail on the Results Processing is found in section S.5 and Figure S12 of the supporting information (SI).

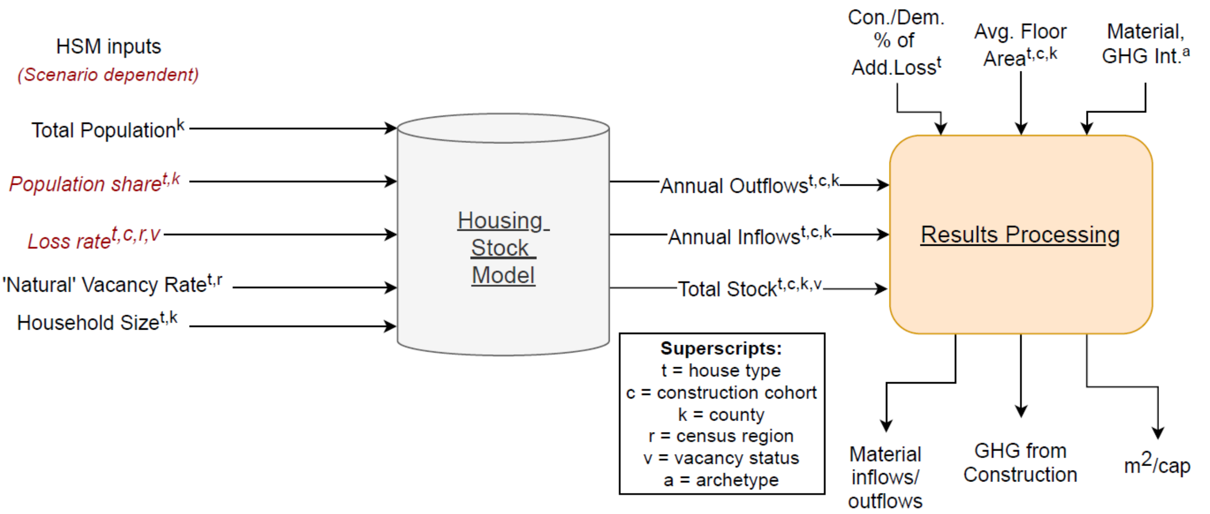

Figure 1 Schematic of inputs and outputs from housing stock model. Con. = Construction; Dem. = Demolition; Add. = Additions; Loss = Losses. Int. = Intensity, referring to material per unit of floor area (kg/m^2), GHG per mass material (kgCO_{2e}/kg), and the resulting GHG per unit floor area (kgCO_{2e}/m^2). 'Results Processing' is further described in Figure S12

Table 1 Housing stock model variables and superscripts

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 Stock with positive OSG	Housing units/Year
A_{-OSG}	Additions to 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 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	3,142 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: 2020-2060

The starting point for our model is 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 (Eq. 1). See Table 1 for definitions of each variable and subscript.

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

We use population projections for US counties 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). We adapt Hauer's SSP2 ("middle of the road") county population projection to 2060, scaled first to the US Census Bureau mid-range national population projection (US Census Bureau, 2017a) (Figure S1) and again to actual US resident population on July 1 2020 (US Census Bureau, 2020c), to bring the projections in line with recent US population levels and projections. We estimate future changes in household size based on data from McCue (2018), and apply the same proportional reduction in household size 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 1-yr and 5-yr population and occupied housing unit estimates for 2019 from the American Community Survey (ACS), Tables B25033 and B25127 (US Census Bureau, 2021). This estimation is elaborated further in Section S.1.1 of the SI.

In the second model step we calculate losses from the housing stock based on annual loss rates, summarized in Table S1. Loss rates for each age-cohort are calculated 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 2000-2009 will be in the 0-19 age range, while others will be in the 20-59 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) (Eq.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, our 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 is 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 (Table S1).

Next we calculate additions to stock, 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 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 stock if the occupied stock does not grow. Our reading of AHS data suggests that this is not necessarily the case. At national and Census Region levels, positive additions to stock occur even in times of negative OSG (Fig. S4). 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. We use a linear model (Table S4) to estimate the addition rate ($AR \geq 0$) conditional on the OSG rate in cases of negative OSG. We then multiply this estimate of *AR* by the total stock to calculate additions to stock in cases of negative OSG, A_{-OSG} (Eq. 3).

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

For cases of positive OSG, we calculate annual additions to stock, A_{+OSG}, as the sum of total stock growth (*TSG*) and losses (*L)* (Eq. 4). Total stock growth equals the product of OSG, a 'natural' vacancy factor (VF_n), and an estimated stock growth factor (*GF*) which defines the ratio of actual total stock growth to vacancy adjusted OSG (Eq. S1).

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

The natural vacancy factor VF_n is defined as total stock divided by 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 stock) in order to move the stock towards the natural vacancy rate. For example, if vacancy rates are below the natural rate, *GF* will be greater than 1, which will increase additions to stock and cause the vacancy rate to increase. If vacancy rates are above the natural rate, *GF* will be less than 1, reducing additions to stock and causing the vacancy rate to decrease. We specify a linear model to estimate *GF* as a linear function of changes in the vacancy factor *dVF* (Fig. S5-S7) based on historical AHS data (US Census Bureau, 2017b, 2020a). We estimate the value of GF 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. $dVF^y = 0.5*(VF_n - VF^y)$. This specification reflects our 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*.

We estimates natural vacancy rates using the mean vacancy rates for each house type and Census Region calculated from AHS data 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 (Figure S8). To describe vacancies in the housing stock in 2020, we calculate vacancy rates 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 initial stock, additions, and losses in year *y* (Eq. 5), and vacancy factors are then calculated as total stock divided by occupied stock, as shown in Eq. 6.

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

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

In order to calculate material flows associated with additions and losses to stock, we first convert additions and losses into new construction and demolition. The portion of additions to 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 (Table S2). For demolition, we assume that on average 35%, 20% and 45% of single-family, multifamily, and manufactured housing losses from stock are due to demolition or disaster (Table S3). The resulting estimates of material inflows 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 we adopt are slightly higher than historical rates (Table S3), as we assume 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 which left the in-use stock in previous years, which are not picked up by AHS statistics). Some remaining houses which leave the stock become 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 SI section S.2. Housing characteristics for Hawaii and Alaska are excluded from the ResStock database, and so our 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 (Figure S12). Combining the occupied floor area data with population estimates, we calculate evolution of floor area per person (m^2/cap) per county and house type. Floor area and population data can then be aggregated to calculate of floor area per person for all house types and/or for larger geographical 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., 2020; Roca-Puigròs et al., 2020). Our approach facilitates the identification of stock characteristics and dynamics that will influence 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 inflows and outflows (Fig S12).

We use Athena Impact Estimator (Athena Sustainable Materials Institute, 2020) to generate material intensities for 51 housing archetypes (described in SI section S.3), and use these to estimate weighted-average material intensities by house type and county for 48 construction materials. To calculate material related GHG intensities, we aggregate to 29 material categories for which we estimate GHG emissions per kg of material production. Material GHG intensities come from a variety of sources including environmental product declarations and life-cycle assessment databases (Jones, 2019; Wernet et al., 2016). We select intensities from the most recent, and US-representative sources where possible. We incorporate GHG emissions from construction site transport and energy use based on archetype-specific estimates from Athena, scaled to be more consistent with literature estimates (Table S7). Archetype characteristics are summarized in Table S6, and the GHG intensity from all materials and construction activities per floor area is shown in Figures S9-S10. 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 is the focus of future research. In this paper we demonstrate 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, we increase the loss rates (Table S1) by a factor 1.5, which is comparable to reducing average lifetime for all housing by one third. In cases of positive OSG, this will directly produce higher stock additions as described in Eq. 4. For negative OSG, we apply the factor of 1.5 to the additions estimated in Eq. 3. In a *High Multifamily* scenario, we increase the share of population living in multifamily by 0.25 percentage points (p.p.) per year in counties where population grows by at least 5% over 20 years between 2020-2040, and 2040-2060. 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, we redefine the floor area distributions so that any new house larger than 279 m^2 (3,000 sqft) is instead in the range of 186-278 m^2 (2,000-2,999 sqft, c.f. Fig. S15). To put this scenario in context of recent trends, between 25-30% of new single-family houses built in the 2010s were 279 m^2 or larger (US Census Bureau, 2020b). In order to fit with scenarios in which residential floor area consumption converges to a range of 30-40 m^2/capita (Grubler et al., 2018; Hertwich et al., 2020), a 279 m^2 house would require 7-9 inhabitants. In 2019, houses of 279 m^2 and larger 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 Reduced Floor Area scenarios (5 and 6), floor area characteristics for new housing in future cohorts is assumed to remain the same as housing built in the 2010s (Fig. S14, S15).

Table 2 Summary description for six housing stock scenarios. multifamily population increases apply only to counties where population growth exceeds 5% over 20 years for 2020-2040, and 2040-2060. FA = Floor Area; p.p = percentage points

Scenario	**1. Baseline**	**2. High Turnover**	**3. High Multifamily**	**4. High Turnover & Multifamily**	**5. Reduced Floor Area**	**6. High Multifamily, Reduced FA**
Loss Rate	Historical rates by region	1.5X Historical rates by region	Historical rates by region	1.5X 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 p.p. per year	Increase 0.25 p.p. per year	2020 share by county	Increase 0.25 p.p. per year
Floor Area Distribution, New Homes	Same as 2010s	Same as 2010s	Same as 2010s	Same as 2010s	No homes > 279 m^2	No homes > 279 m^2

4 Results

4.1 Aggregated National Results

Figure 2 shows annual additions and losses to stock, aggregated to the national level, from 2020 to 2060 for the six housing stock scenarios. In all scenarios, additions to stock are higher than losses, reflecting continual stock growth. In the *High Turnover* scenarios, we see 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.

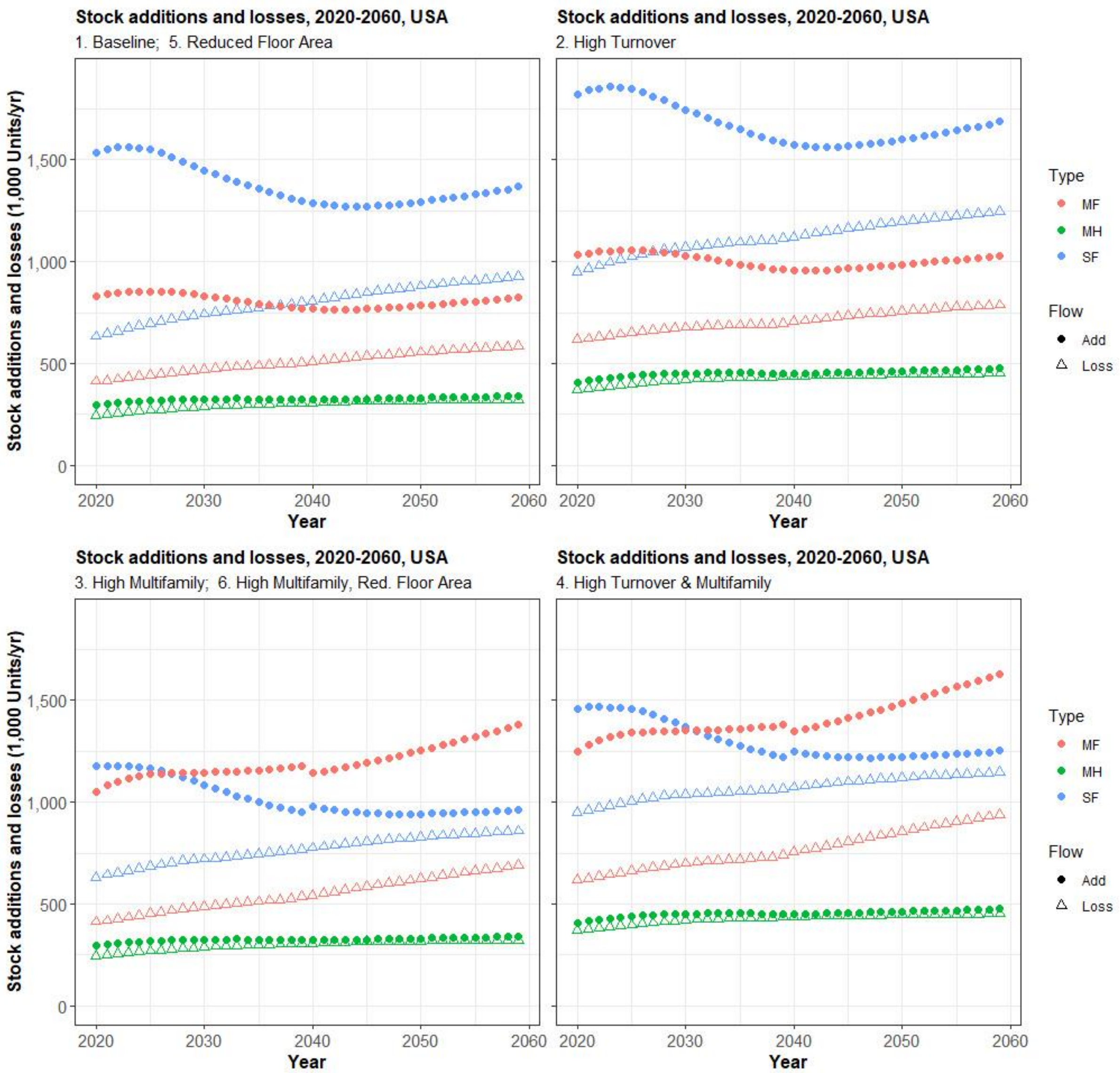

Figure 2 Inflows (additions) and outflows (losses) from stock for three house types for each housing stock scenario.

In Figure 3 we compare the growth of national single-family 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 to 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. 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.

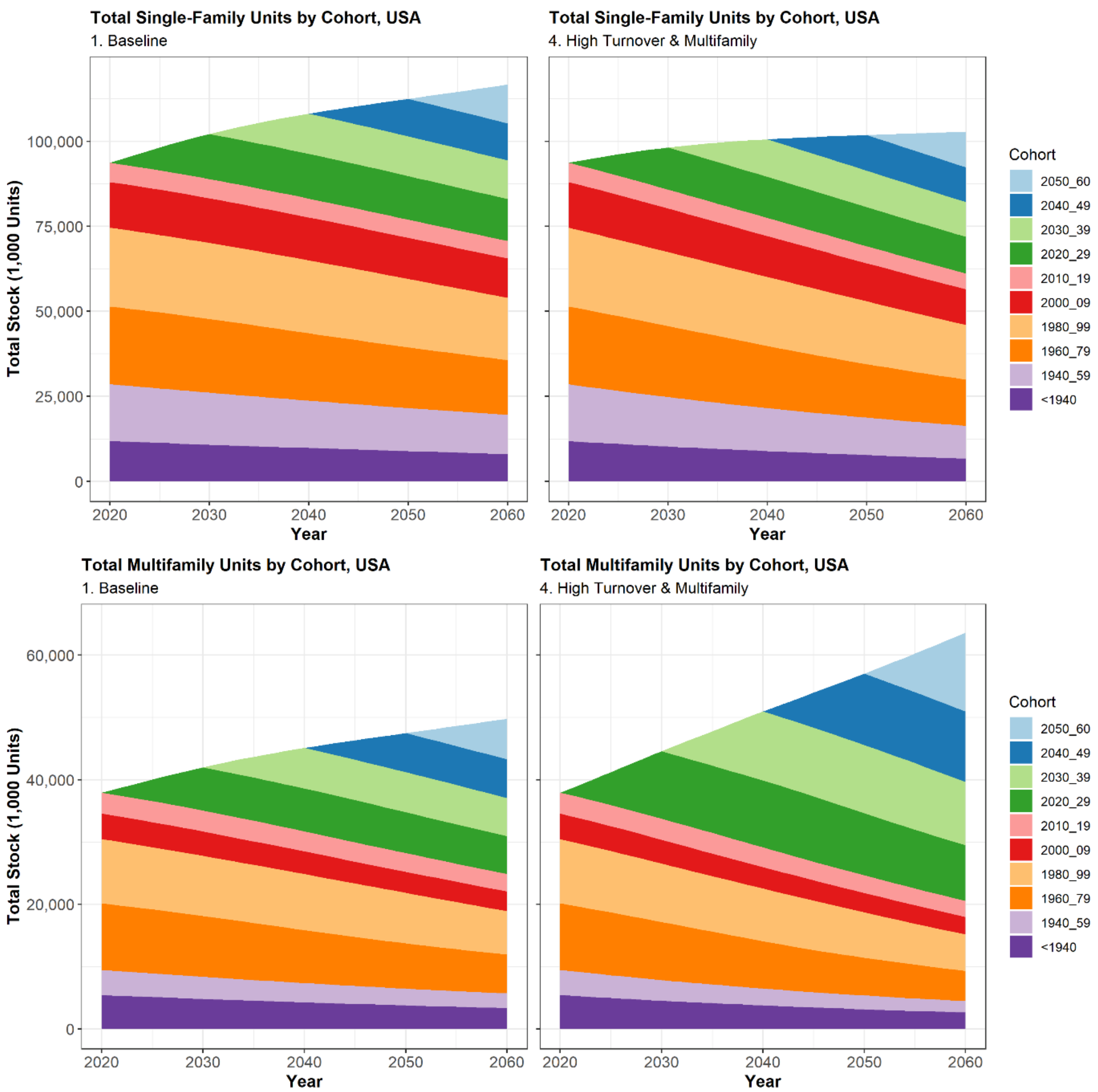

Figure 3 Evolution of single-family and multifamily housing stocks by construction cohort for two scenarios

In Figure 4 we show implications of the housing stock scenarios for evolution of national occupied floor area per person (m^2/cap). In the Baseline scenario, we see steady growth from 60.2 m^2/cap in 2020 to 69.2 m^2/cap by 2060. Although declines in average household size play some role, this growth in m^2/cap is primarily because housing built from 2020 onwards is much larger on average than housing which leaves the stock, which is mostly from the early and mid 1900s (Fig. S14). Speeding up the turnover rate in scenario 2 accelerates this growth, and floor space per person reaches 70.7 m^2/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 m^2/cap by 2060. The Reduced Floor Area scenario shows floor area per person stabilizing at 62.0 m^2/cap from 2040 onwards, while the lowest trajectory is achieved by combining high multifamily and reduced floor area (scenario 6), which reduces floor area per person to 58.9 m^2/cap by 2060. The limited reduction of floor area per person achieved in only one scenario demonstrates the difficulty of reducing m^2/cap only through altering the characteristics of new construction. Floor area consumption in the US is already high by international standards (Ellsworth-Krebs, 2019). We show floor area consumption in 2020 and 2050 for all counties in Figure S24, illustrating the geographical variation in m^2/cap.

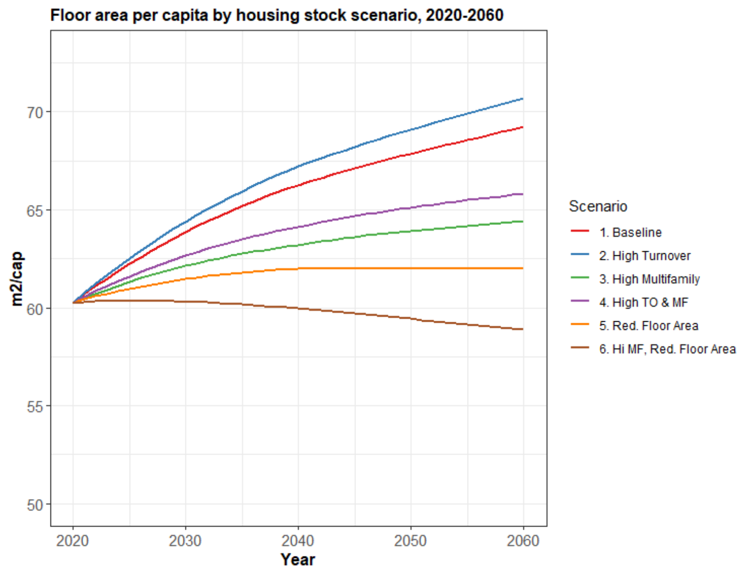

Figure 4 Occupied floor area per person in each housing stock scenario

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 2020-2060 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 2020-2060 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*. SI Figure S16 breaks down emissions by aggregate material and construction categories, demonstrating the prominence of fibreglass-based products (including roofing, window frames and doors), concrete and cement, steel, and transport and site energy.

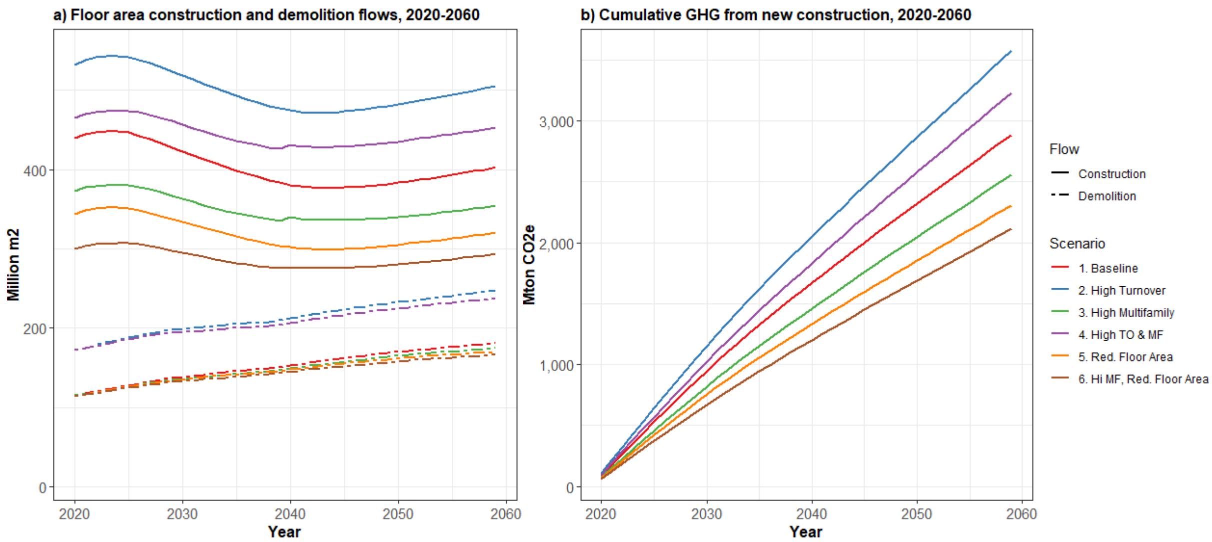

Figure 5 a) Floor area inflows and outflows from construction and demolition, b) Cumulative GHG emissions from new residential construction for five housing stock scenarios

4.2 Selected County Results

We next compare stock model results 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 (Fig S3). Harris County, TX (home to Houston city) is a county with high projected population growth. Providence, RI is a county with low projected population growth. San Juan County, NM, is a county expected to see major population decline, and Marquette County, MI is projected to have modest population decline.

We show the projected total stock of multifamily housing for each of these counties in Figure 6 for the *Baseline* scenario. In Harris County, strong population growth translates into large increases in housing from the new cohorts. In Providence county, we see modest additions of multifamily housing in the new cohorts (much more than additions in the 2000s and 2010s, but still less than additions in the 20th century cohorts), but 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 (Fig S13). 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 (Fig S13), in fast growing counties such as Houston, TX, 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 our formulation for stock additions under negative OSG has no basis in natural vacancy rates, (Eq. 3), there is no mechanism by which natural vacancy rates are achieved in declining counties. To address this, we adjust loss and addition rates to curb excessively high or low vacancy rates (c.f. SI section S.1.2). However, in some cases, even with zero construction vacancy rates can still increase, as exemplified by San Juan, NM. The location of these four counties is indicated in Figure 8.

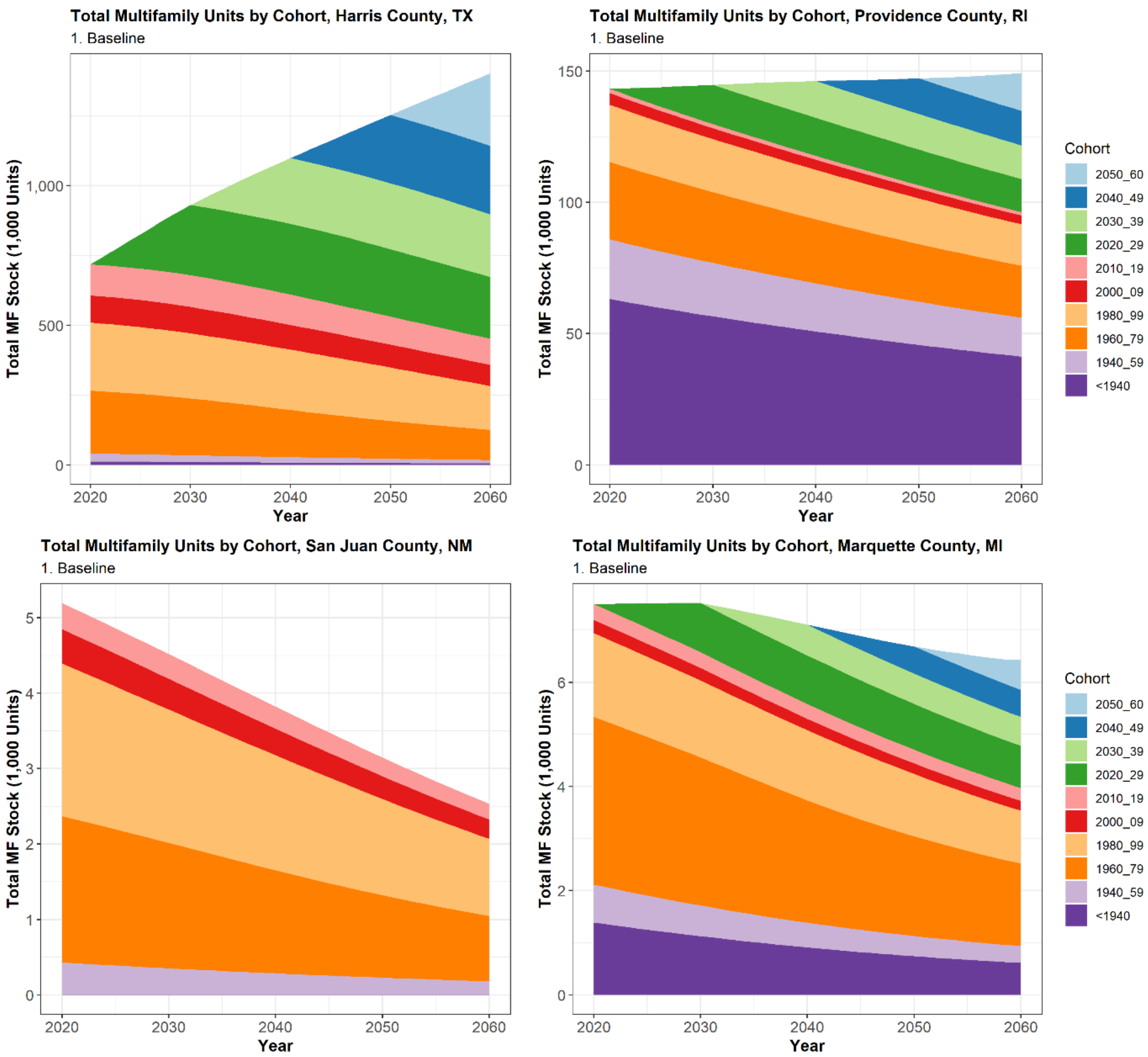

Figure 6 Multifamily stock evolution by construction cohort for selected counties

In Figure 7 we demonstrate inflows 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 (Figure S17). 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), due to the large mass of concrete used in the foundations. Of these four counties, only Harris County, TX, 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, scenarios 2 and 4, or scenarios 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, 6) require the smallest inflows of concrete.

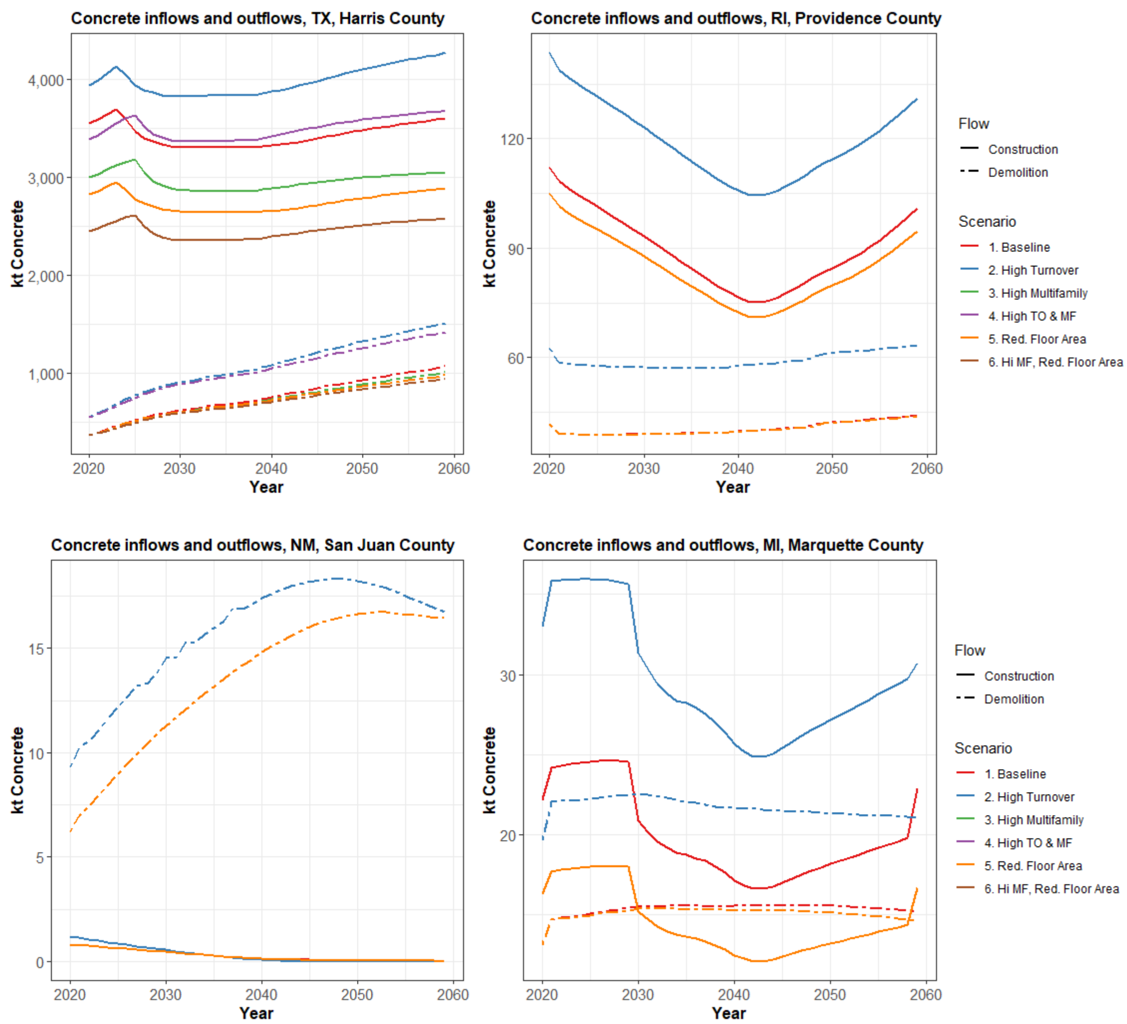

Figure 7 Concrete inflows and outflows in selected counties for five housing stock scenarios. In Providence, San Juan, and Marquette counties, population growth is not high enough to activate the growth of multifamily population shares in high multifamily scenarios, and thus results for Scenarios 1 and 3, Scenarios 2 and 4, and Scenarios 5 and 6 are the same.

The comparison of material inflows and outflows at local level can be used to estimate potential for material re-use within a limited geographic area. Figure 8 we show the ratio of demolition and construction related concrete outflows and inflows for all counties in 2020 and 2040. We show similar figures for concrete and other materials for more years in Figures S18-S20. A substantial number of (brightly coloured) counties have outflows which are higher than inflows in 2020. The prevalence of such counties grows considerably between 2020 and 2040. The darker coloured 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 reuse of waste materials will be far from sufficient to supply the total materials requirements for new construction. In bright coloured 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 re-use 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 (Fig. S21).

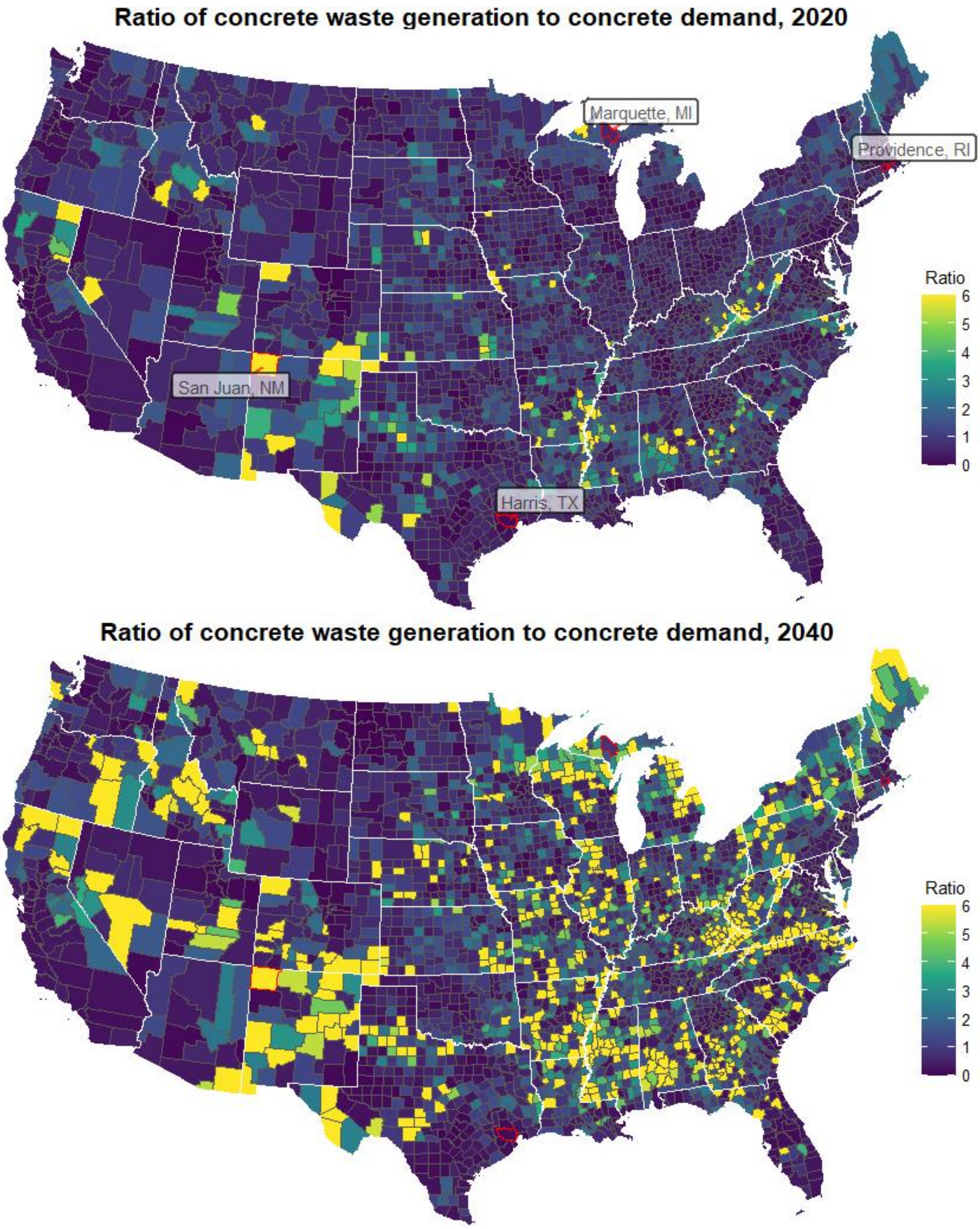

Figure 8 Ratio concrete waste generation to demand for US counties in 2020 and 2040

5 Discussion

Given the long lifetime of housing in the US (most recently estimated as 130 years on average (Ianchenko, Simonen, & Barnes, 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 housing tends to be much larger than older houses which account for the majority of housing stock losses, floor area per person is expected to increase steadily in the *Baseline* scenario (Fig. 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 higher opportunity for material re-use, as the number of redundant vacant units (in excess of the natural vacancy rate) would be reduced (Fig. S23), and their materials would become available for potential re-use. We do not currently model GHG benefits from material recycling or re-use in this model, but this may reduce emissions from construction. The potential for material re-use 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, Gruhler, & Ortlepp, 2017a). Emission reductions from circular re-use of materials are not guaranteed, and depend on many factors including the ability to displace primary material production, local demand for re-use, 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 our 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, Hartley, & Krimmel, 2019) on multifamily and small single-family continues to build. Several city and state governments across the US are considering or moving towards the removal of single-family zoning (Bliss, 2021). Aside from land-use restrictions, federal tax and finance regulations also encourage single-family over multifamily development (Berrill, Gillingham, & Hertwich, 2021), while local property taxes also 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 m^2 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 (de-zoning, 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). Our results make clear the difficult of substantially reducing floor area per person through building smaller new housing alone. In our 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°C (Grubler et al., 2018; Pauliuk et al., 2020; van den Berg et al., 2021). Building smaller homes is necessary to limit 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, Tucker, & Schmidt, 2020).

Developments in material stock and flow modeling have brought about increasing spatial resolution, particularly in studies that combine material flow analyses with GIS (Haberl et al., 2021; Yang et al., 2020). Although the spatial resolution of our housing stock model is lower than GIS-based studies, the geographical unit of US counties is still useful for comparing local-scale material inflows and outflows, and the potential for local material re-use 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 which 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, Effenberger, & Banse, 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. Our specification of housing stock inflows and outflows with reference to locally observed and regional 'natural' vacancy rates represents a novel approach to housing stock modeling, and contributes to the emerging incorporation of vacancy in housing stock models.

We finally discuss limitations of the model, to highlight areas in which this approach can be improved and extended. Although our archetype approach defines material intensities based on many different housing characteristics, we do not consider age dependencies, so otherwise similar old and hew housing archetypes are assumed to have the same material intensity. For vacancy rates, we assumed historical average vacancy rates by house type and Census Division to represent the 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, Hartley, & Krimmel, 2019) could shed light on the role of regulations and implications of future policy changes. Our results of material inflows and outflows are just a first step in assessing potential for material recycling and re-use. Applying the continuous-MFA method would enable estimation of the actual potential for material re-use and related GHG emission reductions. Finally, the results of our 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 lower than the 'mid-range' Census projection that we employ in this study.

6 Conclusions

In this study we present a novel housing stock model for US counties incorporating dynamic vacancy rates, with different scenarios of housing stock growth turnover rates and characteristics to 2060. As the growth of 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 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.

Data Availability Statement

Readers can 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/xxxx/xxxxx [URL withheld for blind peer review]

Competing Interests

The author(s) has/have no competing interests to declare.

Ethics Statement

Ethics approval was not required for this research

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