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Research Paper

Exploring synergies between transit investment and dense redevelopment: A scenario analysis in a rapidly urbanizing landscape

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ABSTRACT

Like many urban areas around the world, Durham and Orange counties in North Carolina, USA are experiencing population growth and sprawl that is putting stress on the transportation system. Light rail and denser transit-oriented development are being considered as possible solutions. However, local agencies and stakeholders are concerned the light rail may worsen housing affordability and have questioned whether investment in both light rail and dense redevelopment are necessary to achieve community goals. We developed an integrated system dynamics model to quantitatively explore the outcomes of these land use and transportation options across multiple societal dimensions. The model incorporates feedbacks among the land, transportation, economic, equity, and energy sectors. This paper uses the results of four model scenarios, run between 2000 and 2040, to address two main questions: (1) what role does redevelopment play in capturing the socioeconomic benefits of transit infrastructure investment? And (2) how do redevelopment and light-rail transit interact to affect housing and transportation affordability? We find that transit investment and dense redevelopment combine synergistically to better achieve the goals of the light-rail line, including economic development, mobility, and compact growth. However, housing affordability does worsen in the combined scenario, as transportation-cost savings are not sufficient to offset the rise in housing costs. We emphasize that model users may input their own assumptions to explore the dynamics of alternative scenarios. We demonstrate how spatially-aggregated systems models can complement traditional land use and transportation models in the regional planning process.

1. Introduction

The Triangle region of North Carolina, USA is a rapidly growing area currently facing a common challenge among cities around the world: a sprawling pattern of growth, leading to a growing separation between people's homes and their workplaces, putting added stress on the transportation system.

To address this issue, a light-rail transit system has been proposed to connect the town of Chapel Hill and city of Durham along a heavily-used commuting corridor (Fig. 1). In conjunction with this proposal, planners are considering rezoning for denser redevelopment around the proposed transit stations in order to concentrate growth and limit sprawl (Triangle Transit, 2012). The stated goals of the light-rail project include promoting economic development, improving mobility, and increasing compact, mixed-use development (Triangle Transit, 2012). However, local agencies and stakeholders are concerned that the light-rail line and associated economic and land development may worsen housing affordability and displace transit-dependent populations (Triangle Transit and TJCOG, 2013).

Local and regional planning organizations have jointly developed detailed land-use allocation and transportation demand models to forecast the impact of alternative transportation and land use scenarios (TJCOG, 2014; TRM Service Bureau and TRM Team, 2012). These are essential for long-range planning. However, because the existing models rely on static land-use, economic, and demographic projections, they do not address feedbacks and synergies caused by complementary policy options, and were not designed to address affordability and environmental impacts.

The Durham-Orange Light Rail Project System Dynamics (D-O LRP SD) model can both help fill this gap locally and demonstrates how spatially aggregated SD models generally can complement current land use and transportation-planning models. It identifies the mutually

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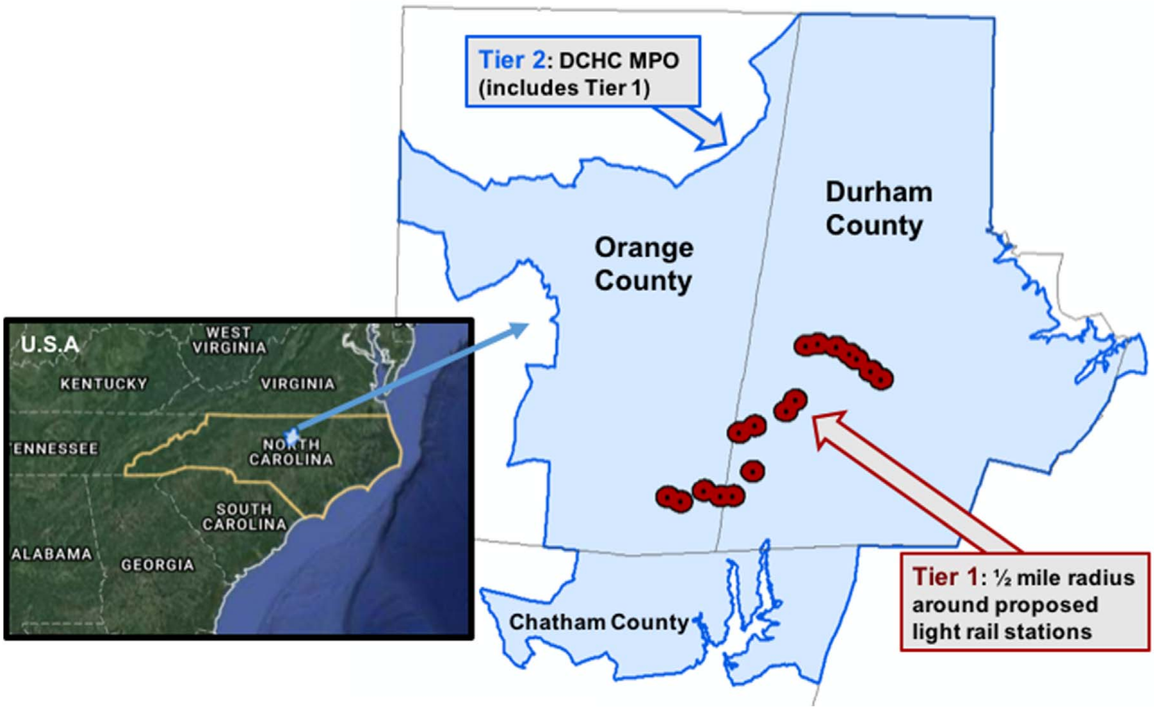

Fig. 1. Map of study area.

reinforcing relationships between compact development and transit investments and their social, economic, and environmental benefits and tradeoffs, and provides a prototype for how similar models could be constructed to suit other cases around the world. In this paper, we use results from four scenarios in the D-O LRP SD model to address two main questions: (1) what role does redevelopment play in capturing the socioeconomic benefits of transit-infrastructure investment? and (2) how do redevelopment and light-rail transit interact to affect housing and transportation affordability?

2. Literature review

Scenarios have been used to explore alternative futures in the land-use planning literature since the 1960s (Doxiades, 1966; Wallace-McHarg Associates, 1964). Though computer modeling has enabled scenarios to become more detailed, complex, and validated, the functions remain the same. Rather than forecast the future, scenario sets serve as a bridge between modelers and stakeholders and stretch users' thinking and perspectives, integrating knowledge to facilitate comprehension of a 'bigger picture' (Xiang & Clarke, 2003). More than just the outputs of computer models, scenario sets are curated from among the thousands possible, and interpreted to provide vivid narratives (Schoemaker, 1995; Xiang & Clarke, 2003). In this way, good scenario sets help to overcome cognitive biases and serve as a platform for consensus-building (Godet, 2000; Schoemaker, 1995; Xiang & Clarke, 2003).

In the 1990s, urban scenario planning began to use models that merged land use and transportation (Bartholomew & Ewing, 2009). Initially, these were treated using separate models, where the outputs of a land use model were used as inputs into a transportation-demand model (Aljoufie, Zuidgeest, Brussel, van Vliet, & van Maarseveen, 2013). However, that approach was limited in its ability to capture the dynamics of land use and transportation systems; relationships were traditionally unidirectional, and therefore did not allow transportation changes to affect land use, and their sequential processing did not allow for internal feedbacks (Haghani, Lee, & Byun, 2003). Increasingly, integrated models that allow bidirectional impacts are being developed, creating a class of tools called land use and transport interaction (LUTI) models (Waddell, 2011; Wegener, 2004).

A review of the literature shows there is growing interest in expanding LUTI models to address their implications for urban sustainability, as indicated by Geurs and Van Wee (2004). They reviewed LUTI models that incorporate sustainability indicators to some degree.

However, this approach has challenges. Because LUTI models require more data from a diversity of fields, it is challenging to quantify several social, economic, and environmental indicators with confidence. Conventional econometric and optimization models excel at simulating spatial and temporal development patterns on the basis of historical data (Santé, García, Miranda, & Crecente, 2010), and are less focused on how socioeconomic factors drive local land use and development (Han, Hayashi, Cao, & Imura, 2009). Geurs and Van Wee, 2004 (2004) concluded that contemporary LUTI models did not address macro-economic impacts of land use and transportation, nor many social or health effects. Finally, conventional models are not designed to address delays among urban activities, as optimization approaches primarily provide information on the optimal state of the system, rather than on transitions. This means that the models assume that urban systems are in a state of equilibrium, which is rarely the case (Haghani et al., 2003; Vina-Arias, 2013).

System Dynamics (SD) models complement traditional LUTI models by providing a simpler framework to capture the dynamic properties of systems through the explicit representation of feedback loops. By focusing on causal relations and simulating "what if" scenarios, they can more easily incorporate a variety of sustainability indicators (Sterman, 2000), and are therefore useful for evaluating responses to policy scenarios on transit investment and development (Han et al., 2009). In addition, their relative simplicity and low data-intensity make it easier to examine demographics, land use, transportation, water, and energy use in an integrated fashion (Rickwood et al., 2007). On the other hand, SD models are not spatially explicit and lack the detail that other models can provide. Therefore, the core contribution of SD models is the provision of a more comprehensive view of the urban system by integrating processes at different time scales (Abbas & Bell, 1994).

One of the first applications of SD was as a method to simulate

Table 1
Statistical Analysis of BAU Scenario Against Data for Selected Tier 1 Variables.

Variable	Historical data source	Historical data R^2 value	Avg absolute% deviation from historical data	Projected data source	Projected data R^2 value	Avg absolute% deviation from projected data
Population	U.S. Census Bureau (U.S. Census Bureau, 2000, 2014)	0.976	0.57%	Triangle Regional Model (TRM) v5 Socioeconomic (SE) Data (DCHC MPO, 2013)	0.999[a]	2.9%[a]
Developed land	Community Viz 2 Parcel Geodatabase (TJCOG, 2014)	Insufficient data points	2.5%	Imagine 2040 Results Grid Data (TJCOG, 2014)	Insufficient data points	4.6%
Nonresidential sq ft	Chatham County Tax Administration Office, 2014; Durham County Tax Administration, 2000–2014; Orange County Tax Administration, 2014	0.999	0.22%	Not Available	N/A	N/A
Single family dwelling units	Chatham County Tax Administration Office, 2014; Durham County Tax Administration, 2000–2014; Orange County Tax Administration, 2014	0.994	0.50%	Not Available	N/A	N/A
Multifamily dwelling units	Chatham County Tax Administration Office, 2014; Durham County Tax Administration, 2000–2014; Orange County Tax Administration, 2014	0.997	0.43%	Not Available	N/A	N/A
Single family property value	Chatham County Tax Administration Office, 2014; Durham County Tax Administration, 2000–2014; Orange County Tax Administration, 2014	0.288	4.3%	Not Available	N/A	N/A
Multifamily property value	Chatham County Tax Administration Office, 2014; Durham County Tax Administration, 2000–2014; Orange County Tax Administration, 2014	0.592	3.0%	Not Available	N/A	N/A
Nonresidential property value	Chatham County Tax Administration Office, 2014; Durham County Tax Administration, 2000–2014; Orange County Tax Administration, 2014	0.267	39%	Not Available	N/A	N/A
Total employment	U.S. Bureau of Economic Analysis (BEA, 2014), U.S. Census Bureau, 2015, and TRM v5 SE data	0.914	1.2%	TRM v5 SE data	1.000	0.18%
Total earnings	Woods & Poole Economics Inc., 2014 and TRM v5 SE data	0.994	1.3%	Woods & Poole Economics Inc., 2014 and TRM v5 SE data	1.000	0.17%
VMT	Not Available	N/A	N/A	TRM v5 travel demand result shapefiles (TRM Service Bureau & TRM Team, 2012)	0.998	1.1%

[a] Population projections were only available for a growth scenario that is comparable to the LRRD scenario, so these values are for the LRRD scenario results, not BAU.

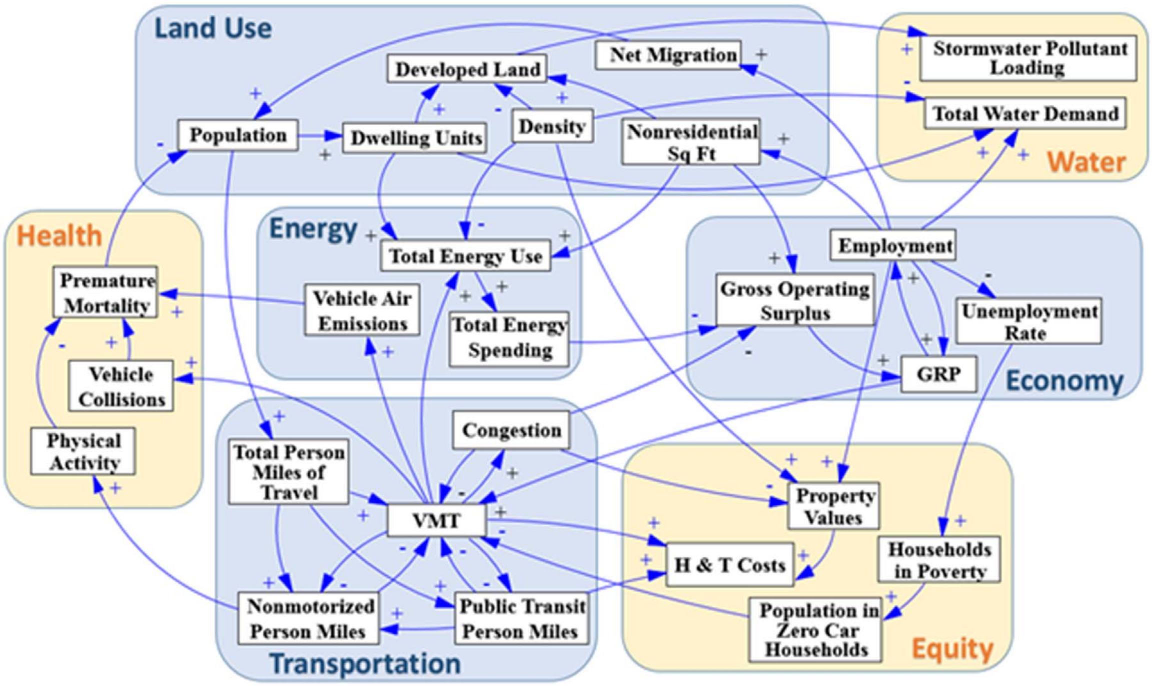

Fig. 2. Simplified CLD of the D-O LRP SD Model with core sectors (blue) and output-oriented sectors (yellow). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

urban growth and change (Forrester, 1969). More recently, SD models have been used to address a variety of issues in urban land use, transportation, and sustainability all around the world. Land use models have addressed housing supply and demand and urban renewal in the Netherlands (Eskinasi, Rouwette, & Vennix, 2009) and the limits of growth under different urban development schemes in Hong Kong (Shen et al., 2009). Transportation-focused models have addressed policies to manage congestion in China (Wang, Lu, & Peng, 2008) and policies to impact bicycling in New Zealand (Macmillan et al., 2014). A few have focused on land use and transportation interactions. Haghani et al. (2003) developed a model to project the impacts of highway expansion on land usage and transportation performance measures in Maryland, USA. Several groundbreaking models have combined elements of cellular-automata models and SD to capture complex dynamics at a granular scale (Han et al., 2009; Lauf, Haase, Hostert, Lakes, & Kleinschmit, 2012; Pfaffenbichler, 2011).

However, there remains a need to integrate social, economic, and environmental dynamics. Few models incorporate land use and transportation interaction with macroeconomic, environmental, and health indicators, allowing for feedbacks among them (Haghani et al., 2003; Wegener, 2004). We take a step towards such an integrated urban-systems model with a model structure that emphasizes feedbacks, integrates multiple urban systems, and allows users to test complementary policies and their benefits and tradeoffs.

3. Methodology

3.1. System dynamics approach

System Dynamics (SD) is a policy-oriented technique that provides a framework for the design of policies and management of systems to achieve improved system behavior (Sterman, 2000). They do not provide predictions of the future, nor are they designed to optimize a system. Instead, SD models allow users to test the direct, indirect, and induced effects of interventions in "what if" scenarios. SD models are characterized by four key properties: limiting factors, delays, nonlinearities, and a feedback-loop structure built on the basis of stocks and flows (Forrester, 1969; Meadows & Wright, 2008; Sterman, 2000).

3.2. Study area and data

The D-O LRP SD model was constructed based on a conceptual model developed in collaboration with stakeholders, including representatives from the regional transit authority and city and county departments of health, stormwater management, land use planning, and transportation planning. The model consists of 7 interdependent sectors: land use, transportation, energy, economy, equity, water, and health.

The model operates at two geographic scales: Tier 2 – defined by the boundary of the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization; and Tier 1 – the combined area of ½-mile-radius zones surrounding each of the proposed light-rail stations (Fig. 1). Tier 2 was chosen due to the high availability of data at this scale, while Tier 1 was chosen as the area likely to show the largest impacts in response to the rail. Model variable outputs are reported for each Tier on an annual basis between 2000 and 2040, with a model time-step of 0.0625 years, though, in this paper, outputs are only discussed for Tier 1. Model scenarios run in only a few seconds on a typical desktop computer.

Partly as a result of the planned light-rail line, there are an abundance of data and projections available for the area through the regional land use and transportation comprehensive planning efforts. In order to make the D-O LRP SD model complementary to these efforts and to ensure consistency across model results, we aligned many assumptions with those used by the regional land-use allocation model (TJCOG, 2014) and the transportation-demand model used for the 2040 Metropolitan Transportation Plans (MTP) (DCHC MPO, 2013; TRM Service Bureau and TRM Team, 2012).

Table 1 includes a selection of the key data sources, both historical and projected, used to initialize, calibrate, and validate the model (BEA, 2014; Chatham County Tax Administration Office, 2014; Durham County Tax Administration, 2000–2014; Orange County Tax Administration, 2014; U.S. Census Bureau, 2000, 2014, 2015). Historical data and local projections were aggregated for the model's two geographic boundaries.

3.3. Model structure and specifications

A causal loop diagram depicting the interconnections among key variables is shown in Fig. 2. Plus (+) signs indicate a positive association between variables, and minus (−) signs indicate a negative association between variables (an increase in A produces a decrease in B). This paper focuses on outcomes in Tier 1 most strongly impacted by changes in the land use sector, however Procter et al. (2017) discusses the energy sector, and forthcoming papers will discuss other model outcomes impacted by changes in the transportation and economy sectors in more depth.

In Fig. 2, the primary cross-sectoral feedback loop involving land use can be seen: employment growth drives growth in nonresidential floor space (measured in square feet (sq ft)), which increases gross operating surplus (GOS, the portion of GRP due to production, not earnings), which raises the gross regional product (GRP), which contributes to an increase in total employment, completing the loop. The limit on total available land in Tier 1 provides a balancing effect, preventing unlimited growth. There are numerous such reinforcing and balancing loops throughout the model. For brevity, we present only the key variables used to estimate land use and affordability in the model.

The Land Use sector comprises three types of stocks: (1) acres of land, (2) dwelling units, and (3) developed nonresidential sq ft of floor space. The Equity sector outputs three key indicators: (1) property values, (2) renter costs, and (3) transportation costs. The categories of disaggregation, as well as driving factors of these key variables, are summarized in Table 2.

Beyond the main drivers of change listed, additional variables mediate the calculation of the key variables. Below, we present equations for those variables crucial to understanding how the key indicators in the land and equity sectors are calculated. Table 3 lists which of the variables used in the calculation of the land use and equity sectors described below are exogenous.

3.3.1. Land sector

The demand for nonresidential floor space (DNFS) is calculated independently for each land use category, following the general equation that is standard in land use planning (Durham City-County Planning Department, 2012):

$$DNFS = E \div ESR$$

Where E is employment, and ESR is the employee space ratio (the average number of employees per sq ft), with values for each of the four categories of nonresidential land use (Table 2). This is converted to acres using floor area ratios (FARs) for each nonresidential land use category, Tier, and scenario.

Demand for single family and multifamily dwelling units (DDU) is calculated separately, using distinct values for each factor in the following equation:

$$DDU = EH + ((PG \times PPH) \div HS) \times (1 + (year \div HL)) \times (1 + SH) \times EV$$

Where EH is the equilibrium households (calculated by the population in households divided by household size), PG is the projected annual population growth over the next 5 years, PPH is the percent of people in households, HS is the household size, HL is the average lifetime of dwelling units, SH is the percent of second homes (applied only to the calculation of single family dwelling units), and EV is the effect of vacancy on the demand for dwelling units. This final variable is an L-shaped curve with a long tail, indicating that very high vacancy decreases demand for dwelling units, but this effect diminishes with lower vacancy rates. These elements ensure there is always some degree of endogenous vacancy in the model; the vacancy rate subsequently affects renter costs in the Equity sector. Demand for dwelling units is converted to demand for residential acres using the average single family or multifamily density for the Tier and scenario, and, in conjunction with demand for nonresidential acres, drives land conversion.

The gap between demand for acres and the actual developed acres, for each land use category, feeds the land conversion flows. The total time for land conversion and construction results in a two-year delay between demand and realization. If the supplies of both agricultural and vacant land are depleted, land conversion and construction cease, constituting a cap on total developed acres, nonresidential floor space,

Table 3
List of Exogenous Variables in the Land Use and Equity Sectors.

Exogenous variables	
Numerical inputs	Policy interventions and demographic shifts
Birth and death rates	Redevelopment of developed land to higher densities
Effect of developed portion of residential land on migration	Light rail line construction
Effect of unemployment on net migration (Tier 1 only)	Residential densities (for new construction)
Employee space ratios (by employment category)	Floor area ratios (by land use type, for new construction)
Percent of people in households	Public transit fare price
Average lifetime of dwelling units	Parking cost of average trip
Percent second homes	Price of gasoline
Effect of vacancy on the demand for dwelling units	Miles per gallon without congestion
Impervious surface coefficients	Earning per employee (by employment category)
Elasticities governing property values	Subsidized dwelling units
Elasticities governing renter costs	Percent of people in single family dwelling units
Percent of MF dwelling units below 75 percent of median renter costs	Household sizes
Poverty threshold	

Table 2
Summary of Primary Variables in the Land Use and Equity Sectors.

Variables	Categories of disaggregation	Main variables driving changes
Land (in acres)	Vacant, Agricultural, Protected Open Space, Right of Way, Retail, Office, Service, Industrial, Single Family, Multifamily	Dwelling Units and Developed Nonresidential Floor Area (in square feet)
Dwelling Units	Single Family, Multifamily	Population, Vacancy rate
Developed Nonresidential Floor Space (in sq ft)	Retail, Office, Service, Industrial	Employment (disaggregated by the same categories)
Property value	Single Family	Lot size, available land, income growth, commute time, retail density, population growth, job density
	Multifamily	Building size, available land, income growth, commute time, retail density, population growth, job density
	Nonresidential	Building size, retail density, employment growth
Renter costs	n/a	MF property value per DU, MF vacancy rate, GRP growth rate
Transportation costs	Fuel cost per VMT, Vehicle ownership and maintenance costs, Parking costs, Transit costs	Price of gasoline, MPG, Vehicle stock, Parking price, Public transit fare price

and dwelling units. While there is ample available land in Tier 2 for years to come, this cap on land does come into play in Tier 1, contributing to nonlinearities in the model results.

Redevelopment operates by allowing users to set a target percent of land that is redeveloped to a target density, achieved gradually, between 2020 and 2040. Acres redeveloped at a higher density in turn reduce desired acres, all else equal, by satisfying more demand for floor space or dwelling units on less land. If desired acres drop below the actual, impervious developed land may become vacant and pervious. The initial conversion of a portion of land to a higher density modestly increases nonresidential floor space in Tier 1, which is then amplified through feedbacks.

Redevelopment can only occur in Tier 1. However, because Tier 1 is part of Tier 2, the proportional reduction in acres and the proportional increase in nonresidential floor space and dwelling units are reflected in Tier 2 outputs. Due to feedbacks in the model, the increase in nonresidential floor space in Tier 1 caused by redevelopment, once added to Tier 2, spurs more growth in GRP, eventually leading to higher demand for floor space in Tier 2, developed at the default density. Densities calculated in the land sector, including nonresidential density per acre, retail density per capita, population density, and intersection density, subsequently affect outcomes in other sectors of the model, including property values, energy use, and transportation mode shares.

3.3.2. Equity sector

The Equity sector has few feedbacks to other sectors of the model; however, it responds to many other sectors and the feedbacks inherent in them. Here, we present the equations for the primary indicators in this sector: property values, renter costs, and transportation costs. Property values are driven by several other variables in the model, which is evident in the equation for multifamily property value per dwelling unit (MV):

$$MV = MV_i \times (r_{vl}^{e_{vl}} \times \left(r_{inc}^{e_{inc}}\right) \times \left(r_{jd}^{e_{jd}}\right) \times \left(r_{rd}^{e_{rd}}\right) \times \left(r_{ct}^{e_{ct}}\right) \times \left(r_{far}^{e_{far}}\right)$$

Where MV_i is the average multifamily (MF) property value per dwelling unit (DU) in the initial year (2000). We then include six drivers (relative to their initial values in 2000, *r)* and their respective elasticities (*e*): vacant land, an indicator of land scarcity (r_{vl}), resident per capita net earnings (r_{inc}), job density (r_{jd}), retail density (r_{rd}), commute time (r_{ct}), and nonresidential FAR (r_{far}). Many of these relative values are calculated in other sectors of the model; for example, commute time is calculated in the transportation sector.

Single family (SF) property value per DU and nonresidential property value per sq ft are calculated similarly, although the drivers for each vary somewhat, according to relationships found in the literature. SF property value responds to SF densities rather than nonresidential density. Nonresidential property value only responds to relative employment, nonresidential density per acre, and retail density per capita.

Renter costs per household (*RC*) are derived primarily from multifamily housing costs, because most renters in the area are in apartments:

$$RC = RC_i \times \left(r_{mvr}^{e_{mvr}}\right) \times \left(r_{mv}^{e_{mv}}\right) \times \left(E_{grp}^{r_{grp}}\right)$$

RC_i is the initial renter costs per household. Three drivers are included with their respective elasticities (e) and effect tables (E): relative MF vacancy rate (r_{mvr}), relative MF property value (r_{mv}), and annual change in the grp growth rate (r_{grp}).

Calibration of property values and renter costs was accomplished through a combination of a diverse set of elasticities obtained from the literature (Capozza, Hendershott, Mack, & Mayer, 2002; Dobson & Goddard, 1992; Heikkila, Gordon, Kim, Peiser, & Richarson, 1989; Jud & Winkler, 2002; Kain & Quigley, 1970; Kockelman, 1997; Srour, Kockelman, & Dunn, 2002; Vina-Arias, 2013). In a several cases, these elasticities had to be modified to fit the study area, as many studies provide elasticities for either one metro area or an average for

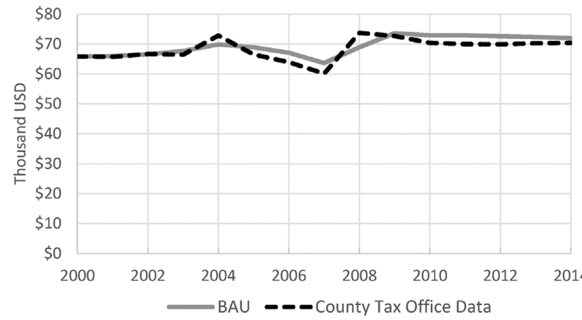

Fig. 3. Multifamily property value per DU in BAU scenario compared to historical data 2000–2014 in Tier 1. R^2 of 0.59 and average absolute percent deviation of 3%.

the nation, and none were found that were specific to the study area. For example, while an elasticity of +1.09 between population growth and single family property values from a study at the metropolitan level (Jud & Winkler, 2002) worked well for Tier 2, that was too strong of a relationship for Tier 1, where it had to be adjusted down to +0.5. Details of the calibration and validation can be found in EPA et al. (2016).

Finally, transportation costs are a sum of parking costs, vehicle fuel costs, vehicle ownership and maintenance costs, and transit fares.

3.4. Model validation and sensitivity testing

BAU scenario results for more than 20 key variables were validated against historical and projected data at both Tiers, both visually (by plotting results and data in a graph) and statistically. Table 1 shows the R^2 value and average absolute percent deviation for a selection of variables at Tier 1. Several variables, including population and VMT, were also validated under the LRRD scenario against local projections under a comparable growth scenario. Fig. 3 shows a data series comparing multifamily property value, one of the variables with a lower R^2 value, against historical data. This is a key contributor to renter costs in the model and demonstrates the degree of uncertainty in this output.

Extensive sensitivity testing was also performed to further evaluate the validity of the model results. Twenty structural and extreme-condition tests were performed on central variables and elements in the model, where variables were either removed or set to extreme values to determine which best reproduced historical trends. Elements from the land and equity sectors tested include land development, the effect of vacancy on the demand for dwelling units, property value elasticities, and an extreme population test. Fifteen behavioral and policy sensitivity tests were performed on variables that either were uncertain due to limited historical data or that were key policy interventions, such as the effect of the LRT on the demand for nonresidential sq ft, the percent of net migration to Tier 1 due to the LRT that is external to Tier 2, the effect of vacant land on property value, the elasticity of MF property value to building size, and the effect of jobs per commercial acre on parking costs. The results of these last three tests are described below in the Discussion section. See EPA et al. (2016) for the full model description, validation, and sensitivity testing.

4. Results

4.1. Scenarios

Four main scenarios were run in the D-O LRP SD model to simulate the most likely transportation and land use options for Tier 1 between 2020 and 2040, the impacts of which are also reflected at Tier 2. First, the Business As Usual (BAU) scenario simulates what would happen if current demographic, land use, and transportation trends were to continue and serves as a baseline scenario for comparison. Nonresidential and residential densities remain constant at their average values in 2014.

Second, the Light Rail (LR) scenario simulates the construction of the proposed 17-mile light rail transit (LRT) line between Durham and Chapel Hill beginning in 2020 and completed by 2026, and assumes that the LRT line (1) motivates more people to use public transit than would an equal number of bus service miles, (2) causes a 10% increase in demand for nonresidential (excluding industrial) floor space, (3) increases the share of new jobs that goes to unemployed residents of Tier 1 rather than to commuters, from 5% to 10%, and (4) increases net migration in Tier 2 by 1.5 times the increase in Tier 1, on the assumption that additional growth will happen just outside Tier 1. An increase in demand for nonresidential floor space within a ½-mile range of station areas, demonstrated through higher property values, is supported in the literature (Cervero & Duncan, 2002; Debrezion, Pels, & Rietveld, 2007; Fogarty, Austin, & Center for Transit-Oriented Development, 2011; Garrett, 2004), as is an increase in the desirability of living near transit stations (Billings, 2011; Yan, Delmelle, & Duncan, 2012), although the magnitude varies widely and depends on local conditions.

Third, the Redevelopment (RD) scenario simulates the implementation of zoning to encourage land redevelopment and higher density in the ½-mile areas that may become station areas. It assumes (1) that, starting in 2020, 20% of developed land is aimed to be redeveloped to almost three times its existing density by 2040, and (2) that the share of the population living in single family dwelling units declines over time in Tier 1, to 25% by 2040, as opposed to remaining stable at 30.9%, as it does in the BAU scenario. The assumed redevelopment density and decline in the share of single family dwelling units aligns with the assumptions used in the regional land-use allocation model (Green, 2015).

Fourth, the Light Rail + Redevelopment (LRRD) scenario includes the assumptions tied to both the LR and the RD scenarios, and is the scenario that most closely aligns with the 2040 MTP.

4.2. Effects of redevelopment and light rail

The LR scenario forecasts improvements in economic indicators, particularly in Tier 1, the immediate station areas (results are only presented for Tier 1). The assumed increase in demand for nonresidential floor space acts through a positive feedback loop with GOS and GRP to increase employment (Fig. 2). By 2040, employment is 15% higher in the LR scenario than in BAU (Fig. 4). Employment growth in turn feeds back to increase nonresidential floor space above the original 10% increase to 13% in 2040. Employment growth also spurs immigration, leading to growth in dwelling units. However, because this development takes place at current densities, developed land grows quickly and soon consumes all available land in the Tier, leading to a plateau in development (Fig. 5). In contrast, the RD scenario, in the absence of the rail, does not assume an increase in nonresidential floor space and therefore leads to limited growth relative to BAU. In fact, the RD scenario causes a decline in developed land between 2020 and 2040 (Fig. 5), as the increase in density is sufficient to return some developed land to vacant land. Land is used more efficiently in the RD scenario, however, with GRP per acre increasing 33% over BAU by 2040. In contrast, the combination of the increase in demand for nonresidential floor space due to the LRT and the gradual redevelopment of 20% of developed land by 2040 to nearly triple the current density in the LRRD scenario allows for the increase in demand to be met while avoiding the consumption of all land in Tier 1. As a result, in the LRRD scenario, by 2040, nonresidential floor space is 35% higher than in BAU, compared to only 13% higher in LR and 4% higher in RD (Fig. 4). Acres of developed nonresidential land are only 4% higher than in the BAU case, relative to 13% higher in LR and 20% lower in RD. Employment is 23% higher than in the BAU case, relative to only 15% higher in LR and 3% higher in RD (Fig. 4). In the short term, growth in developed land slows in response to densification. However, due to the feedbacks described above, developed land in the LRRD scenario surpasses BAU by 2040, though GRP per acre is 28% higher than BAU (Fig. 5).

Increased economic activity in the model leads to an increase in property values, particularly nonresidential property value per sq ft. It is 87% higher than BAU in 2040 in the combined LRRD scenario, in contrast to 15% higher in LR and 38% higher in RD (Fig. 4). In addition, increased employment drives down the unemployment rate and stimulates new migration to the area. The resulting population increase leads to the construction of dwelling units in excess of the increase in employment, positively affecting the jobs-housing balance, a common metric of mixed-uses. The jobs-housing balance declines by 2% in the BAU case between 2020 and 2040 (making it more imbalanced), and the balance changes little in the LR and RD scenarios alone. However, in the LRRD scenario, by 2040, the balance is 3.7% higher than BAU, reflecting a more balanced state (Fig. 4).

The LRRD scenario forecasts large increases in transit and nonmotorized travel, relative to BAU. Public transit travel by residents per capita (which includes bus transit) increases 172% between 2020 and 2040 in the LR scenario, and 176% in the LRRD scenario (Fig. 6). The light rail shifts mode share away from driving; between 2020 and 2040 vehicle travel by residents per capita declines 2% in the LR scenario and 1% in the LRRD scenario, relative to a 5% increase in BAU. While the introduction of the light rail has the largest effect on transit ridership and nonmotorized travel, due in part to the assumption that each public

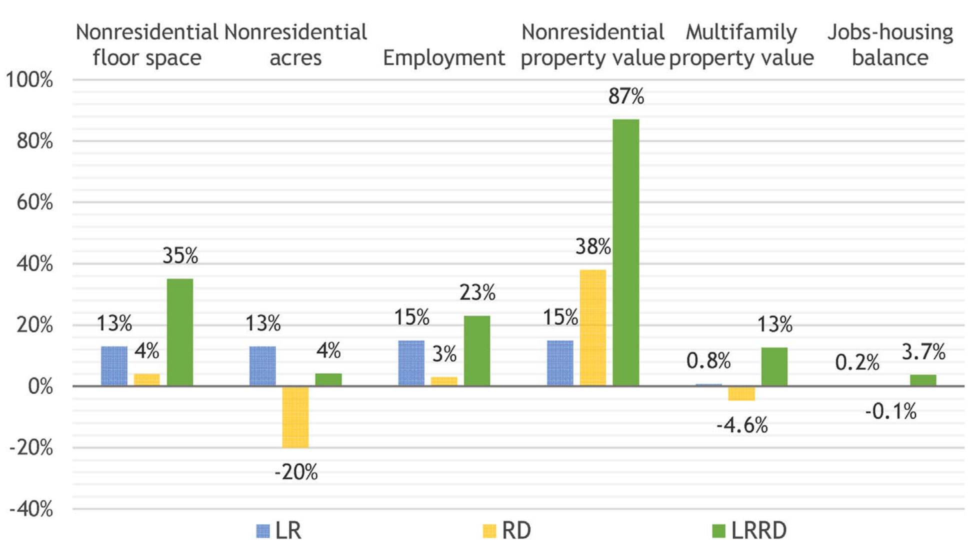

Fig. 4. Percent difference from BAU in 2040 at Tier 1 for Light Rail, Redevelopment, and Light Rail + Redevelopment scenarios.

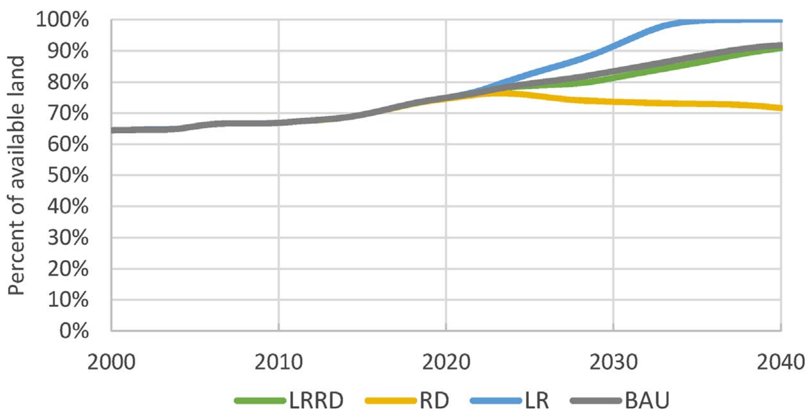

Fig. 5. Developed land as a percent of available land 2000–2040 in Tier 1 for BAU, RD, LR, and LRRD scenarios.

transit trip includes a ½ mile of nonmotorized travel, the RD scenario also contributes. Whereas in BAU public transit travel per capita declines 13% between 2020 and 2040, it only declines 11% in the RD scenario (Fig. 6). Similarly, nonmotorized travel per capita declines 9% in the BAU scenario, relative to only a 5% decline in the RD scenario and a 3% decline in the LRRD scenario.

4.3. Effects on housing and transportation affordability

With increases in jobs, business revenues, density, and accessibility the station areas become more desirable, causing property values to increase, in turn driving an increase in renter and owner housing costs. Multifamily property value per DU is 13% higher in the LRRD scenario than BAU by 2040, compared to 1% higher in the LR scenario and 4.6% lower in the RD scenario (Fig. 4). Single family property value per DU is more stable, at only 2.2% higher in the LRRD scenario by 2040.

Multifamily property value per dwelling unit is the primary contributor to the estimation of renter housing costs. Cumulatively, over the 2020–2040 period, the average renter is forecasted to pay $8956 more than BAU under the LR scenario, $4504 less in the RD scenario, and $13,608 more in the combined scenario (or, $648 more, on average, annually) (Fig. 7). Average transportation costs also rise in the RD and LRRD scenarios, primarily due to a rise in parking costs. Cumulatively, between 2020 and 2040, the average multifamily household is expected to spend $871 less on transportation costs in the LR scenario than in the BAU, $2027 more in RD, and $643 more in the combined LRRD scenario (or, $31 more, on average, annually).

Determining affordability, however, requires more than just costs; it is a function of costs relative to income. Therefore, we calculate an affordability index for lower-income earners in multifamily households by dividing a per-capita retail earnings indicator by a per-capita housing and transportation costs indicator. Because the exogenous projection for per-capita retail earnings rises over time in all scenarios, the affordability index improves in all scenarios. However, in the LRRD scenario, it increases only 2% during 2020–2040, relative to a 4% increase in the BAU case (Fig. 8).

The rising employment rate in the LRRD scenario causes a corresponding drop in the poverty rate. This dynamic represents two possible phenomena: rising employment may employ some previously unemployed residents, but increasing economic prosperity may also displace poorer residents. The lower poverty rate causes a smaller share of households with zero cars in the model, a proxy for transit-dependent households. By 2040, the percent of households with zero cars is 11% in LRRD, compared to 14% in BAU, both down from 16% in 2020.

5. Discussion

5.1. What role does redevelopment play in capturing the socioeconomic benefits of transit infrastructure investment?

5.1.1. Light rail alone

Local communities sometimes resist the densification planned to occur in conjunction with transit projects. However, our model shows that without the density increase that redevelopment brings, the light rail has reduced potential to stimulate economic development, a stated goal of the project. Our default assumption is that investment in the

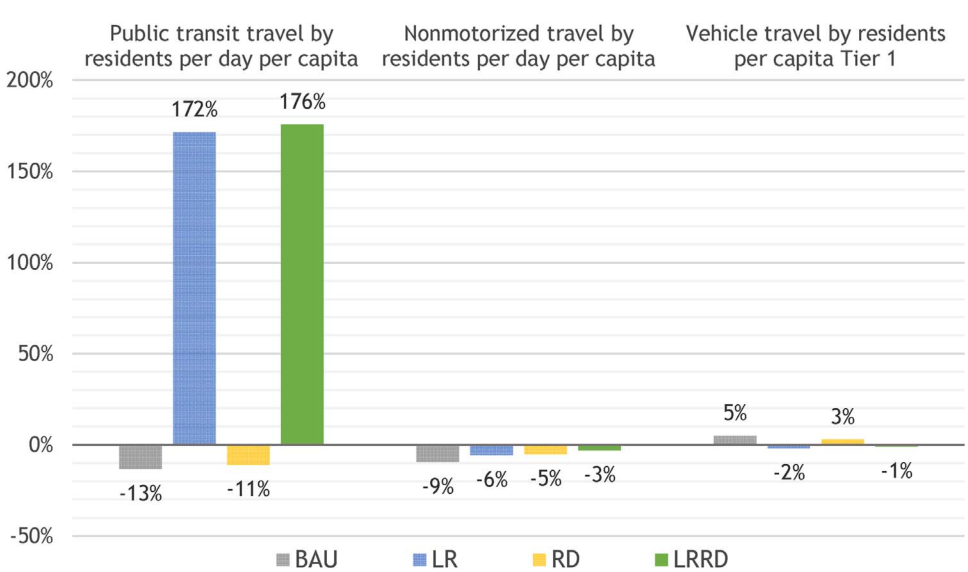

Fig. 6. Percent change in person miles by mode 2020–2040 in Tier 1 for BAU, Redevelopment, and Light Rail + Redevelopment scenarios.

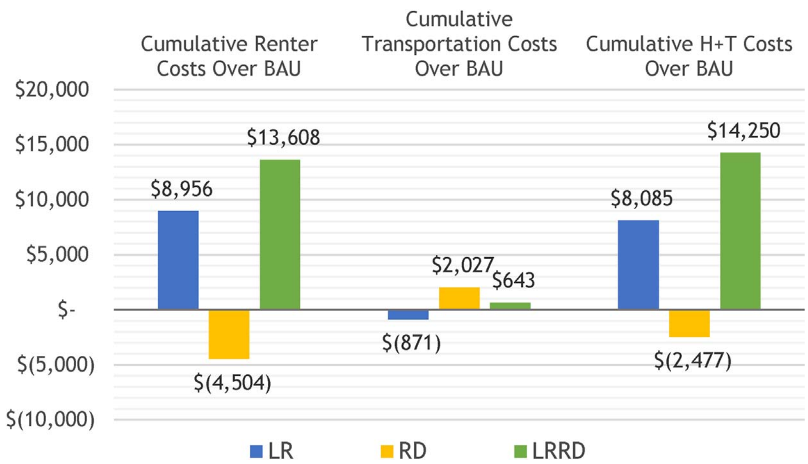

Fig. 7. Cumulative costs (2010 dollars) 2020–2040 relative to BAU in Tier 1 per multifamily household for LR, RD, and LRRD scenarios.

light-rail line spurs 10% more demand for nonresidential development in the ½-mile-radius station areas. Were this additional development to take place at the current average density and no redevelopment of existing parcels took place, as the LR scenario simulates, available land within the ½-mile walking distance of the transit stations would be depleted long before all the demand is met. When this limit on land expansion is met, in 2033, employment growth slows and net migration declines (Fig. 5).

5.1.2. *Redevelopment alone*

There are benefits from developing compactly in the absence of transit; however, our model results confirm what local planners highlight: compact development is most effective in achieving economic development and improved mobility when pursued in conjunction with transit (Durham City-County Planning Department, 2016). Our model forecasts that redevelopment without light rail fails to stimulate employment and population growth. Without some stimulus to demand for nonresidential floor space, whether through light rail investment or otherwise, employment, GRP, and other economic development indicators in the RD scenario remain similar to BAU throughout the simulation.

5.1.3. *Combined effects*

When combined, the RD and the LR scenarios unlock larger changes in key indicators than either does in isolation. First, the untapped economic potential in the final 7 years of the LR scenario is realized. This leads to greater than additive impacts in the LRRD scenario. By 2040, nonresidential floor space in Tier 1 is greater than BAU, by more than the sum of the increase over BAU in the LR scenario and in the RD scenario (Fig. 4). This higher square footage, made possible by the increased density in the RD scenario assumptions, in turn produces higher economic development, leading to higher employment. By 2040, employment and nonresidential property value per sq ft are also higher, relative to BAU, than in the LR and the RD scenarios summed.

Second, the LRRD scenario improves mobility by alternative modes disproportionately, with a more than additive increase in transit use and nonmotorized travel per capita. While the opening of the light rail causes most of the increase to both indicators, the RD scenario also contributes (Fig. 6). In the BAU scenario, transit travel per capita and nonmotorized travel per capita both decline because fuel efficiency is projected to increase, which lowers the cost of automobile travel and increases driving relative to transit use. However, both the LR and RD scenarios blunt this decline. Because the RD scenario increases both population density and the density of pedestrian-friendly intersections, it leads to an increase in the mode shares of transit and walking.

Finally, the LRRD scenario develops more land compactly and decreases the separation between jobs and housing in more than an additive fashion. In the station areas, there are currently far more jobs than dwelling units, causing an imbalance in the numbers of people living and working there. The jobs-housing balance is a metric used in the planning literature as an indicator of mixed uses (Ewing & Cervero, 2010). This balance increases, reflecting more mixed uses, under the LRRD scenario relative to BAU due to the relationship in the model between employment growth and immigration. The nonresidential demand stimulated by the light rail, combined with the expansion in capacity allowed by redevelopment, generates a sufficient employment gap to bring in higher numbers of residents. In addition, the unemployment rate drops, making the area more desirable and increasing

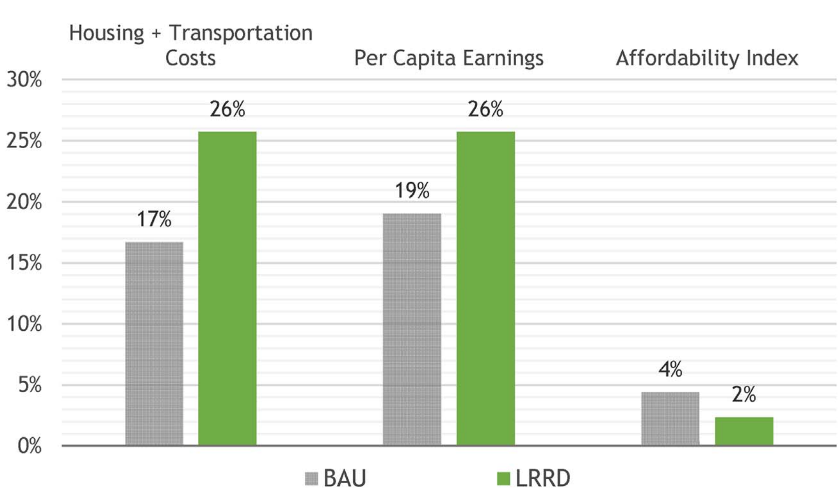

Fig. 8. Percent change in affordability measures 2020–2040 in Tier 1 for BAU and LRRD scenarios.

Sensitivity test	Average Annual Difference in Cost from BAU between 2020 and 2040 in Tier 1*		
	Renter costs per HH	Transportation Costs per HH	Renter and Transportation Costs per HH
LRRD scenario before sensitivity testing	$680	$32	$713
Effect of vacant land on SF property value when scarce -50%	$755	$0	$788
Effect of vacant land on SF property value when scarce +50%	$595	$0	$627
Elasticity of MF property value to building size Tier 1 -50%	$519	$0	$551
Elasticity of MF property value to building size Tier 1 +50%	$812	$0	$844
Effect of jobs per commercial acre on parking cost -50%	$0	$22	$703
Effect of jobs per commercial acre on parking cost +50%	$0	$42	$722

** All values are the difference between the LRRD and BAU, both running the same sensitivity test*

Fig. 9. Sensitivity of housing and transportation costs to key assumptions.

net migration. With more people come more dwelling units. Neither the LR nor the RD scenario in isolation can achieve this effect. Although the jobs-housing balance increases slightly in the short-term in the LR scenario, it reverses course by 2035 as the land cap is reached and employment and population growth slows. In the RD scenario, the jobs-housing balance declines between 2020 and 2040 because there is little more economic growth than in the BAU scenario; unemployment remains about the same as in BAU, and there is little new incentive for immigration. However, when the immigration of the LR scenario is combined with the higher allowable density of the RD scenario, sufficient numbers of new residents increase the jobs-housing balance, representing an increase in mixed uses.

Therefore, the interaction of the economic growth and transportation effects of a fixed light-rail line combined with dense redevelopment better accomplishes the goals of the project. Without a light-rail investment, redevelopment is unlikely to succeed in achieving the project goals, such as economic growth, increased mobility, or compact, mixed-use development (Triangle Transit, 2012). This synergy between the two complementary scenarios is a finding that would not have been possible in a traditional sequential land use and transportation model setting without feedbacks among the land use, economy, and transportation sectors.

5.2. *How do redevelopment and light-rail transit interact to affect housing and transportation affordability?*

The forecasted rise in housing costs following the construction of LRT confirms a main community concern – that with the benefits of light rail will come a reduction in affordability, potentially displacing longtime residents and those groups most likely to ride the rail – the less affluent and the transit-dependent (Horsch, 2015; Triangle Transit and TJCOG, 2013). In our model, one of the most significant factors affecting residential property values is land scarcity (Capozza et al., 2002), which in the LR scenario, drives up the cost of housing. Therefore, policy interventions that relieve pressure on land scarcity may have the largest mitigating impact on housing costs. The RD scenario achieves this in two ways: first, dense redevelopment, and second, a higher proportion of multifamily dwellings. This effect is obvious in the RD scenario, but in the LRRD scenario the mitigating effect of dense redevelopment is outweighed by (1) additional development sufficient to make land similarly scarce as in BAU, (2) the positive effect of rising incomes on property values, and (3) the relationship between higher average building sizes (FAR) and property values.

There is great interest in the potential for transit to lower transportation costs sufficiently to offset higher housing costs in transit-oriented developments (Center for Neighborhood Technology, 2010). In this case, our model projects that does not occur. In the LR scenario, transportation costs do drop relative to BAU, as residents are expected to drive less after the introduction of rail service. However, transportation costs make up only about 30% of total housing and transportation costs, so this drop cannot significantly offset the rise in housing costs. Furthermore, in the RD and LRRD scenarios, given our assumptions, transportation costs rise. Higher density is associated with higher parking costs, driving up average transportation costs per household by more than the savings produced by those choosing to take the light rail line instead. In the LRRD scenario, transportation-cost changes have relatively little impact on overall housing and transportation costs. Over the 20-year period between 2020 and 2040, cumulatively, including both renter housing and transportation costs, the average multifamily household in Tier 1 is projected to spend $14,250 more in the LRRD scenario than in BAU, or $713 more on average annually (Fig. 7).

There is some uncertainty in this result. Due to a lack of historical or projected data for renter and transportation costs, we validated model results for these variables indirectly by validating key inputs. Multifamily property value, the primary contributor to renter costs, was validated against historical data and had an R^2 of 0.59 and an average absolute deviation of 3% (Table 1). We also ran sensitivity tests on three of the key contributors to renter housing and transportation costs: the effects of land scarcity and of building size on multifamily property value, and the effect of jobs per commercial acre on parking costs (Fig. 9). The effects were varied along the estimated range of uncertainty, plus and minus 50%. Outputs are shown for renter costs, transportation costs, and the two combined. Though the magnitude varied, all tests found the same result: transportation costs were never lower than BAU, and therefore were not sufficient to offset housing cost increases.

Note, however, that these figures apply only to the average household. As the Center for Neighborhood Technologies has demonstrated with their Housing + Transportation Index (2010), whether transit reduces transportation costs sufficiently to outweigh housing cost increases heavily depends on the characteristics of the household, including car ownership, location of residence, income bracket, and more. Because, in our model, transportation costs rise in the redevelopment scenarios primarily due to parking costs, the costs for households without a car would be much lower. To comprehensively address the effects of the rail on housing and transportation costs, disaggregation of households by car ownership and income brackets would be necessary.

While affordability still improves between 2020 and 2040 in the LRRD scenario, it suffers relative to BAU. Local employment and average incomes are projected to rise relative to BAU (Fig. 8). However, not only do household costs also rise, but they rise more than average incomes, relative to BAU. This finding confirms community concerns regarding affordability and corroborates the need for an emphasis on expanding subsidized and workforce housing in the station areas. Not only is this an issue of equity, but also one of ridership. Lower income populations are more likely to be transit-dependent and therefore to become regular riders of the light rail line. Economic growth attracts wealthier residents and worsening affordability may force a disproportionate number of transit-dependent residents to leave, decreasing ridership. In our model, by 2040, the percent of households with zero cars is 3 percentage points lower in LRRD than in BAU. While local governments' ability to control the affordability of housing is limited, policies to encourage density and the construction of multi-family housing may help keep housing costs down, not only by providing more affordably sized homes, but also by relieving the pressure of land scarcity on property values. Conversely, raising the minimum wage would improve affordability in the face of rising costs. Our model approach provides an opportunity to test the impact of such changes, and view the new equilibriums achieved.

5.3. Limitations of the model and research gaps

The D-O LRP SD model has several limitations. First, the model is not spatially explicit beyond the two urban-scale tiers discussed. Therefore, redevelopment is portrayed only as densification; we cannot determine the extent to which land use patterns such as clustering may impact outcomes. Second, density in our model is a policy input. While this is intentional, to allow planners and stakeholders to test the impact of varying levels of compact development, it means density is not driven by internal mechanisms. Therefore, the model cannot be used to determine how concentration of development in the city center affects development at the periphery. Finally, relationships in the model are governed by the best available literature, but, in many cases, such as elasticities governing property values, uncertainty is high. In these cases, sensitivity analyses of the key relationships help address this problem by evaluating the impact of the uncertainty and providing a range of results. Nonetheless, model results present the best available estimate of magnitude and direction of change, but should not be considered predictive.

There is a need for further research to disaggregate population subgroups, such as by vehicle ownership and income brackets, to make it possible to model household costs and displacement more accurately. In addition, more localized and verified elasticities with respect to property values and transportation costs would improve model accuracy and confidence. Finally, there is a need for research to determine transferability of the model structure to other cases.

6. Conclusions

The D-O LRP SD model can help identify the mutually reinforcing relationships between compact development and transit investments and their socio-economic benefits and tradeoffs. Our results strongly indicate that transit investment and compact development combine synergistically to better achieve many of the goals of the LRT project, including economic development, improved mobility, and compact, mixed-use development. Nonetheless, the combined scenario does increase housing costs the most, suggesting a need for an effort to address affordability if both the light rail line and dense redevelopment are pursued.

The D-O LRP SD model fills a gap in integrated modeling for urban planning and provides an example of how spatially aggregated SD models can complement current land use and transportation model used in the urban planning process. Traditional models, while essential, are very data- and time-intensive, and therefore make it more difficult to connect land use and transportation decisions to economic, social, or environmental endpoints, much less allow those impacts to feed back and affect land use and transportation indicators, as occurs in this model. Furthermore, while traditional methods of stakeholder interaction tend to be more qualitative, our approach provides a quantitative tool for planners to assess the social, economic, and environmental outcomes of a range of possible policy and demographic scenarios. Feedbacks ensure that economic and social indicators are not only outcomes, but also impact land use and transportation. Outputs for each year of the model run allow users to calculate cumulative impacts and assess nonlinear responses. Because the inputs and assumptions are quickly and easily modified on the fly, the model can be used as a tool for education and consensus-building with stakeholders and the public. Finally, the model provides a prototype for how similar models could be constructed to suit other cases around the world.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.landurbplan.2017.07.021.

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