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Integrating Land Use and Socioeconomic Factors into Scenario-Based Travel Demand and Carbon Emission Impact Study

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Abstract Integration of land use and transportation planning with current and future spatial distributions of population and employment is a challenge but critical to sustainable planning outcomes. The challenge is specific to how sustainability factors (e.g., carbon dioxide emission), and land use and socioeconomic changes are considered in a streamlined manner. To address the challenge, this paper presents an integrated modeling and computing framework for systemic analysis of regional- and project-level transportation environmental impacts for land use mix patterns and associated transportation activities. A synthetic computing platform has been developed to facilitate the scenario-based quantitative analysis of cause-and-effect mechanisms between land use changes and/or traffic management and control strategies, their impacts on traffic mobility and the environment. Within the integrated platform, multiple models for land use pattern, travel demand forecasting, traffic simulation, vehicle and carbon emission, and other operation and sustainability measures are integrated using mathematical models in a Geographical Information System environment. Furthermore, a case study of the Greater Cincinnati area at regional level is performed to test the integrated functionality as a capable tool for urban planning, transportation and environmental analysis. The case study results indicate that such an integration investigation can help assess strategies in land use planning and transportation systems management for improved sustainability.

Keywords Integration · Land use · Socioeconomic factor · Travel demand · Transportation environmental sustainability · Carbon emission

1 Background and Research Motivation

Environmentally sustainable planning greatly relies on the support of synthetic analysis by using models that integrate land use and transportation planning, dwelling and

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employment-related spatial distributions, as well as other related social economy factors. However, such an integration is scarce in practice [1– 4]. The challenge appears specific to the need of integrating sustainability factors (e.g., transportation carbon emission), and land use and socioeconomic factors into the development process. [3–6]. Some previous studies revealed that core models to be incorporated in the integration include the land use model, travel demand forecasting model, vehicle emission, and microscopic traffic simulation model [3, 7, 8]. The best integration is to interconnect and imbed those models through data flows in a Geographical Information System (GIS) environment [3, 4, 9, 10].

Recent studies suggested that land use pattern and associated economic changes influence travel behavior and demand. Performance can be measured by vehicle miles travelled (VMT), vehicle hours travelled (VHT), and vehicle emissions over roadway networks. All these variables are impacted by travel patterns or travel behaviors which are closely linked with land use density, diversity, and accessibility [8, 11–15]. Land use density is measured by the population and employment in a given geographical unit (i.e., census tracts, traffic analysis zones, etc.). High densities are often associated with high accessibility to opportunity sites [16].

Strong mismatch between the locations of jobs and houses possibly results in much longer commuting distances. To reduce commuting cost (measured by combined travel distance and time), it is an ideal planning to layout houses, working places, and services close to each other (i.e., mixed-use development pattern). Accessibility is usually measured as the distance of a location relative to the regional urban center, or the number of jobs available within a given travel distance or time. Accessibility was found to exert a strong influence on per capita VMT [17, 18]. Dispersing employment to suburban locations is associated with increasing per capita vehicle travel [5, 19, 21]. Cervero and Duncan [22] found that the accessibility was negatively associated with the VMT and VHT.

The activity-based travel demand forecasting (TDF) approach views travel demand as a derived demand from the need to pursue activities distributed in space and time [23]. To date, some studies have been conducted to compare the modeling results between the traditional four-step TDF models and activity-based TDF models. Ferdous et al. [24] evaluated the performance of those two models at regional-level and project-level analyses using the data collected in the Columbus metropolitan area, Ohio. The results indicated that activity-based model outperformed overall the four-step model in the region-level analysis. Shan et al.'s study [25] using the data gained in Tampa Bay Region indicated that the activity-based model is more capable of capturing the non-home based trips than the four-step model.

Emission factors are empirical functional relations between the mass of vehicle emissions and the involved vehicle activities [26–32]. The environmental effect of the traffic management with advanced technologies (e.g., ramp metering, connected vehicle technology) can be depicted by environmental measures (e.g., emission rates and inventories, fuel consumptions). A critical step of estimating values of the measures is to obtain emission factors of the concerned pollutants and apply them to vehicle activities as estimated from traffic simulation. The MOVES model is usually used to provide emission rates in the USA [33].

In light of the above understanding, the paper presents a scenario-based integrated approach to examine interactions between land use development, transportation activities, and mobile emission for sustainability analysis in an integrated simulation platform. Within the platform, categorized models—travel forecasting model, vehicle emission model and microscopic traffic simulation model are integrated heuristically mathematically with data flows via input/output (I/O) interfaces. A case analysis is used to demonstrate the functionality testing of the integrated approach with the data obtained in the Greater Cincinnati area, USA.

The paper is organized as follows: The background and research motivation is followed by the literature review and related work. Then, the research methodology is presented with introduction of major associated mathematical models to be involved in the integrated platform system. The case study demonstrates major analysis functionality of the system with the data obtained from the Greater Cincinnati area. Finally, a summary of the research is presented.

2 Research Methodology

2.1 Methodological Framework

As shown by Fig. 1, the conceptual hierarchy of the categorized models includes the land use pattern, travel demand forecasting, and carbon emission estimation and they will be interconnected through input and output data flows. In other words, each involved model will be heuristically "assembled" through clarifying their I/O relationships. For example, land use and social economic data are input to travel demand forecasting model to estimate travel trips, including VMT and VHT. The travel forecasting outcomes provide some inputs to the emission model. Some models may be "zoomed in" smaller parts, which cannot be shown by Fig. 1. For example, vehicle specific power (VSP) in KW/ton, the instantaneous tractive

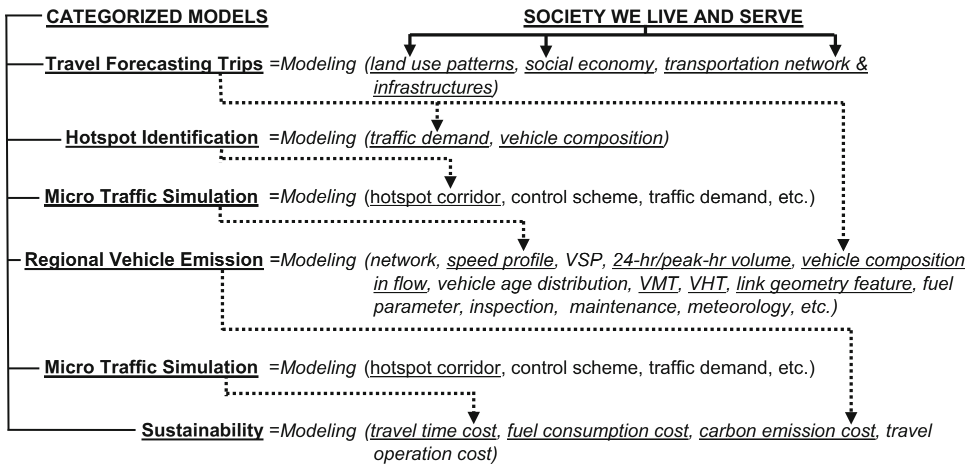


Fig. 1 Conceptual hierarchy of integrated categorized models

power per unit vehicle mass, is a well-acceptable explanation variable in microscopic emission modeling to directly relate it with the emission rate [29, 33–37]. VSP is sensitive to speed and acceleration changes. The acceleration is associated with grades of highways and vehicle masses, and the grades are also associated with topography features [6, 33, 38, 39]. All "Functions" as indicated by Fig. 1 are mathematically developed, and all models are integrated into GIS environment.

2.2 Land Use Pattern

The land use pattern is quantitatively depicted by measurements of density, diversity, and accessibility. Density is measured as the gross population rate of residents and employment within designated geographical units over the gross area [40, 41]. Traffic analysis zones (TAZs) is used as the gross area unit in the study. The overall urban density is calculated as the summation of urban population and employment divided by the gross area of the urban area [42], as expressed by Eq. (1).

$$\text{Density} = (\text{Pop} + \text{Emp})/\text{Area} \tag{1}$$

where Pop is the number of residents in a TAZ, persons; Emp is the number of jobs in a TAZ, jobs; and Area is the TAZ area, mile^2.

The land use diversity or land use mix is measured by the job-population balance (jobpop) and degree of job mixing (jobmix) to reflect the relative balance between jobs and population and diversity of jobs, respectively [43]. Job-population balance represents the degree of self-sufficiency achieved in a community and is used to measure land use mix in many studies and applications [8, 44, 45]. In a compact land use development policy, it is hoped to make jobs and housing distributions balanced by planning the residential and employment areas within close communities. Job-population balance at the regional level is defined as the ratio of employment to population, as expressed by Eq. (2) [46].

$$\begin{aligned}\text{jobpop} = \sum_{i=0}^{n} (1 - |J_i - \text{JP} \times P_i|)/(J_i + \text{JP} \times P_i|) \\ \times ((BJ_i + BP_i)/(\text{TJ} + \text{TP}))\end{aligned} \tag{2}$$

where i is the TAZ number; n is the number of TAZs in the study region; J is the number of jobs in the TAZ; P is the number of residents in the TAZ; JP is the average job to population ratio in the study area; TJ is the total jobs in the county; TP is the number of total population in the study are.

The degree of job mixing quantifies homogeneity of employment land use (i.e., retail, service, industry). To measure such mix degree, an entropy formula is applied, and the degree of job mixing is computed as Eq. (3) [46].

$$\begin{aligned}\text{jobmix} = \sum_{i=0}^{n} \sum_{j} (P_j \times \ln(P_j))/\ln(m) \\ \times ((BJ_i + BP_i)/(\text{TJ} + \text{TP}))\end{aligned} \tag{3}$$

where j is the job category number; P_j is the proportion of jth job category in a TAZ; m is the number of job categories.

The degree of job mixing ranges from 0 to 1. A degree of job mixing with a value more approximating to 1 indicates a higher mix.

Accessibility reflects the ability of people to access to different destinations. Many factors affect accessibility, including mobility, quality and affordability of transportation service options, transportation system connectivity, and land use patterns. The accessibility index is constructed from a very popular functional form for the gravity model [18], in which the accessibility is measured as the ratio of jobs to transportation cost to all possible TAZs expressed as Eq. (4).

$$\mathrm{acce} = \sum_{s=0}^{n} J_s / f(t_{rs}) \quad (4)$$

where $f(t_{rs})$ is the impedance function between two TAZs, r and s; J_s is the number of jobs in the TAZ s.

For ease of interpretation, accessibility values are normalized on a scale from 0 to 1 by dividing the computed accessibility index for each TAZ by the highest accessibility value in a region [42].

2.3 Regional Travel Demand Estimation Through Activity-Based Modeling

The activity-based model is validated with the Household Travel Survey (HTS) data that was conducted in 2009–2010 Cincinnati GPS-based Household Travel Survey [47]. And the model is embedded into the VISUM simulation environment via it external coding module. The structure of the activity-based travel demand model is illustrated by Fig. 2. Activity patterns can be identified based on travelers' socioeconomic status. Then, the tour destinations and modes are predicted by possibility of choosing each destination and mode, respectively. The probabilities are calculated with nested multinomial logit (NML) model [48]. Next, a trip table containing number of trips between TAZs is generated, and then used as the input to the traffic assignment process. Finally, trips between TAZs are loaded to the roadway network.

In the activity-based travel demand model, a person's daily activities are grouped into a set of tours (or trip chains). A tour is assumed to have a primary activity and destination that is the major motivation for the journey [49]. Those tours are tied together by an overarching activity pattern while being constrained by the choice of activity pattern. The structure of the activity patterns can be illustrated by Fig. 3. Discrete choice models based on the principle of utility maximization have become the primary method for modeling activity and travel choices [48]. The utility is assumed to consist of a systematic component that can be estimated as a function of explanatory variables [50–52]. The variables include: (1) socioeconomic variables, i.e., household size, income, car ownership, and personal status (employed, students, unemployed), lifecycle, etc.; (2) land use variables, i.e., area type, employment (number of jobs by job type, i.e., industry, service, and retail), and number of households, etc.; and (3) transportation system variables, i.e., travel

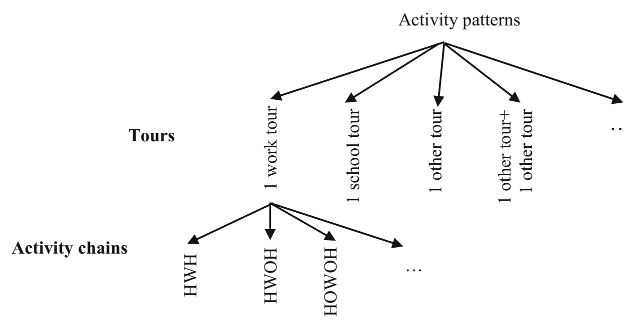
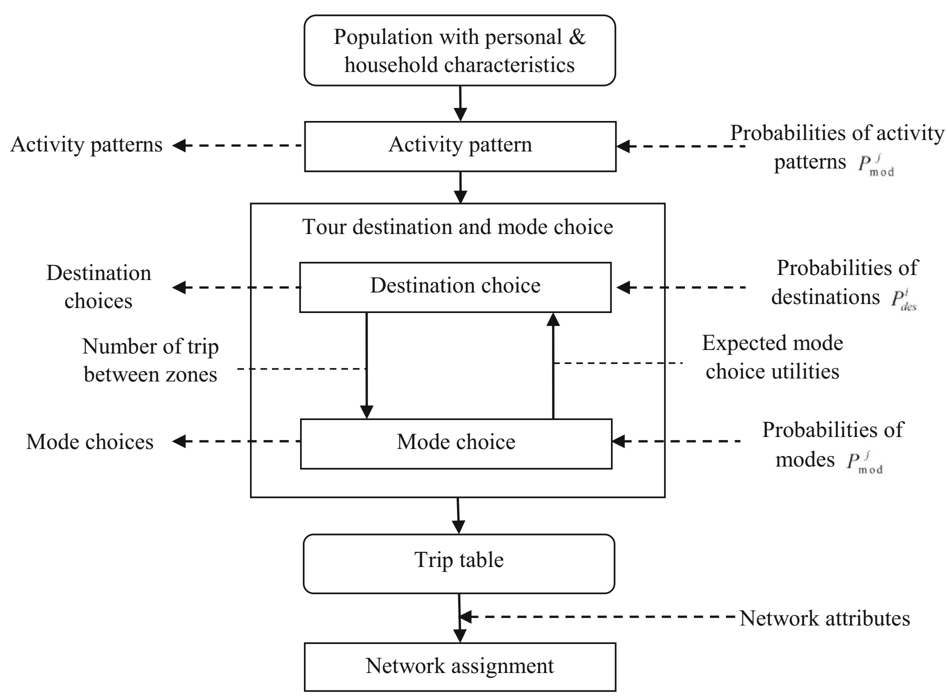


Fig. 3 Structure of activity patterns

Fig. 2 Structure of developed activity-based TDF modeling procedure



time, and travel cost of a transportation system, etc. With the utility of activity pattern, destination, and transportation mode, the travel choices are often modeled by structured logit models such as multinomial logit (MNL), nested logit (NL) [48].

Activity pattern probabilities ($P^{n|m}_{\mathrm{actp}}$) structured as a NL model [48, 49] are calculated by Eqs. (5) through (7).

$$P^{n|m}_{\mathrm{actp}} = P^{m}_{\mathrm{touc}} \times P^{n}_{\mathrm{actc}} \tag{5}$$

$$P^{m}_{\mathrm{touc}} = \exp\left(U^{m}_{\mathrm{touc}}\right) / \sum_{n} \exp\left(U^{m}_{\mathrm{touc}}\right) \tag{6}$$

$$P^{n}_{\mathrm{actc}} = \exp\left(U^{n}_{\mathrm{actc}}\right) / \sum_{n} \exp\left(U^{n}_{\mathrm{actc}}\right) \tag{7}$$

where U^{m}_{touc} and P^{m}_{touc} are the utility and probability of mth tour combination, respectively; U^{n}_{toua} and P^{n}_{toua} are the utility and probability of nth activity chain combination, respectively; $P^{n|m}_{\mathrm{actp}}$ is the probability to choose nth activity chain combination under mth tour combination.

Utilities of the activity chain combinations are defined as a linear function of personal and household attributes and tour activities combination constant; similarly, utilities of tour combinations are defined as a linear function of the natural logarithm sum of utilities of activity chain combinations and tour combination constant [49].

Utilities of tour combinations are defined as a linear function of the natural logarithm sum of utilities of activity chain combinations LOGSUM_m and tour combination constant $\mathrm{CONSTANT}_m$.

$$U^{m}_{\mathrm{touc}} = b_m \times \mathrm{LOGSUM}_m + \mathrm{CONSTANT}_m \tag{8}$$

$$\mathrm{LOGSUM}_m = \ln \sum_{n|m} \exp\left(U^{n}_{\mathrm{actc}}\right) \tag{9}$$

$$U^{n}_{\mathrm{actc}} = a1 \times \mathrm{HHSIZE} + a2 \times \mathrm{TOTVEH} + a3 \times \mathrm{INCOME} + \mathrm{CONSTANT}_n \tag{10}$$

where HHSIZE is the number of person in a household; TOTVEH is the number of vehicle owned by a household; INCOME is the household income, 1 = Less than \$25,000, 2 = \$25,000 to \$49,999, 3 = \$50,000 to \$74,999, and 4 = \$75,000 or above; $\mathrm{CONSTANT}_n$ is the constant of nth activity chain combination.

The probability of choosing destination i (P^{i}_{des}) is calculated with a MNL model [50]:

$$P^{i}_{\mathrm{des}} = \exp\left(U^{i}_{\mathrm{des}}\right) / \sum_{i} \exp\left(U^{i}_{\mathrm{des}}\right) \tag{11}$$

$$U^{i}_{\mathrm{des}} = c1 \times \mathrm{HH} + c2 \times \mathrm{INDUSTRY} + c3 \times \mathrm{SERVICE} + c4 \times \mathrm{RETAIL} + c5 \times \mathrm{SCENROLL} + c6 \times \mathrm{AREATYPE} + c7 \times \mathrm{LOGSUM} \tag{12}$$

$$\mathrm{LOGSUM} = \ln \sum_{j} \exp\left(U^{j}_{\mathrm{mod}}\right) \tag{13}$$

where HH is the number of household; INDUSTRY is the number of industry jobs; SERVICE is the number of service jobs; RETAIL is the number of retail jobs; SCENROLL is the school enrollment; AREATYPE is the area type: 1 = CBD&urban, 2 = suburban, 3 = rural; LOGSUM is defined as expected mode choice utilities, as the natural logarithm sum of the mode choice utility.

The mode choice probability of alternative transportation mode j is calculated with the MNL model [50]:

$$P^{j}_{\mathrm{mod}} = \exp\left(U^{j}_{\mathrm{mod}}\right) / \sum_{j} \exp\left(U^{j}_{\mathrm{mod}}\right) \tag{14}$$

$$U^{j}_{\mathrm{mod}} = d1 \times \mathrm{Time} + \mathrm{Constan}\, t_j \tag{15}$$

where U^{j}_{mod} is the utility of the mode choice; T_i is the travel time, min; $\mathrm{Constant}_j$ is the constant of transportation mode j.

The above models are embedded into a travel demand simulation environment. In this study, it is implemented in VISUM by coding the associated algorithm into the computing programs via COM open source function. The simulated network traffic assignment and other derived variable from the simulation will be merged into the performance system.

In addition to the travel trips resulting from running the TDF model, other mobility performance measurements such as average demand/capacity (D/C) ratio, total delay, daily VMT, daily VHT will be derived from the TDF outcomes to measure the effectiveness of the traffic operation. The VMT is defined by the US government as a measurement of miles travelled by vehicles in a specified region for a specified time period. VHT is the total vehicle hours expended traveling on the roadway network in a specified area during a specified time period. In general, smaller VMT per capita reflects decreased travel demand. High VHT per capita mean longer travel time to be needed, thus reflects lower mobility efficiency. Therefore, a good planning is supposed to result in both smaller VMT and VHT per capita.

2.4 Integrated Evaluation of Environmental Conservation Related Sustainability

Regional-level sustainable analysis involves the estimate of the travel patterns and equivalent vehicle carbon dioxide (CO_2) emission in the context of changes in land use, population, employment, and school enrollment distributions under a given scenario. With the base sociodemographics, the target land uses are derived from the sociodemographic projection under a certain land use development alternative. The target land use and associated sociodemographics, together with geographical TAZ information and transportation infrastructure, are used as inputs to the TDF model. The TDF process estimates travel behaviors, and roadway traffic information. Then, the calculated roadway traffic data are used as input of transportation activities for the emission estimation model (i.e., MOVES in the study) to simulate regional CO_2 emission.

Environmental conservation is one of the important goals in building sustainable transportation systems. It is referred to the natural resources saved or expended. The transportation sector has been reported to contribute more than 25% of GHGs emissions in the United States, which is a looming threat of climate change [53]. It is necessary to target the reduction of vehicle related CO_2 emission and decreasing the use of fossil fuels through reducing travel demand as objectives of the environment conservation. Besides the environmental objectives, social equity and economic development are two another goals need to be considered in transportation planning. The social equity goal aims to improve the mobility and accessibility to allow travelers to save money. The total travel time is an aggregate measurement of mobility and accessibility, which are concerned in the social equity. Economic development reflects direct economic impacts of transportation systems in operation, or management, and relevant environmental impact. Therefore, associated costs of CO_2 equivalent, fuel consumption, and total travel time are adopted as the measurements to evaluate the transportation sustainability. Calculations of these costs are represented through Eqs. (16)–(19). Based on these measurements, a link-based traffic operation cost (Travel operation cost, \$) is developed to synthesize the monetary value derived from travel time, fuel consumption, and carbon cost, as shown by Eq. (20).

$$\text{Travel timecost}_i = \text{VOT} \times \text{VO} \times \text{Volume}_i \times \text{Time}_i \tag{16}$$

$$\text{Fuel consumption cost}_i = \text{Volume}_i \times L_i \times \text{FE}_i \times \text{Price}_{\text{Gas}} \tag{17}$$

$$\text{FE}_i = -0.0066 \times \text{Speed}_i^2 + 0.823 \times \text{Speed}_i + 6.01577 \tag{18}$$

$$\text{Carbon cost}_i = \text{CO}_2 \text{ equivalent}_i \times c \tag{19}$$

$$\begin{aligned}\text{Travel operation cost} = \sum_i (&\text{Travel time cost}_i \\ &+ \text{Fuel consumption}_i \\ &+ \text{Carbon cost}_i)\end{aligned} \tag{20}$$

where i is the number of a roadway link; Travel time cost_i is the cost associated with total travel time of all travelers traversing on link i, \$; VO is the vehicle occupancy; Volume_i is the number of vehicle on ith link, pcu; VOT is the average value of time, \$; Time_i is the average vehicle travel time on ith link, h; Fuel consumption cost_i is the cost associated with the total fuel consumption of all vehicles traversing on link i, \$; L_i is the length of link i, mile; FE_i is the average fuel economy calculation, mpg, which is used to estimate the difference in fuel consumption of the vehicles and is calculated by the regression equation from the fuel efficiency data provided from the MOVES model [6]; Speed_i is the average vehicle speed on ith link, mph; $\text{Price}_{\text{Gas}}$ is the gas price, \$/gallon; Carbon cost_i is the cost associated with the CO_2 equivalent emitted by all vehicles traversing on link i, \$; CO_2 equivalent_i is the total amount of vehicle CO_2 equivalent on link i, US ton, which is calculated by MOVES using link-based traffic volume, speed, and geometry, etc., as inputs; c is the unit cost of CO_2 equivalent, US\$/US ton.

3 Case Study

3.1 Regional-Level Scenarios of Land Use Development Given Increased Population and Employment

The Great Cincinnati area is a metropolitan area with a total of almost 2 million population geographically residing in eight counties in state of Ohio, Kentucky and Indiana, respectively. The Great Cincinnati area is chosen as the case study area. Year 2010 is used as the baseline year. Scenarios are developed by introducing projected changes in population and employment of the study area compared with the baseline year. To investigate the travel demand impact of land use due to such socioeconomic changes, we use density, land use mix, one-center and multi-center urban structure to depict land use pattern. The land use pattern, sociodemographics, and transportation infrastructures for year 2010 are used as the baseline datasets. Based on consulted information from the local metropolitan planning organization, it is implicated that 15% increase in population, employment, and school enrollment by year 2030 is a reasonable assumption for the scenario-based analysis. Based on this assumption, three scenarios are devised, as shown in Fig. 6:

- Planning for single employment-oriented-center development (S1),
- Planning for single mixed-center-oriented development (S2), and
- Two-mixed-center-oriented development (S3).

In S1, only single center is developed, and the majority of the increase employment is allocated to the center while increased population is dwelled beyond the center area. In S2, compared with S1, both increased employment and population and school enrollment as well are assumed to

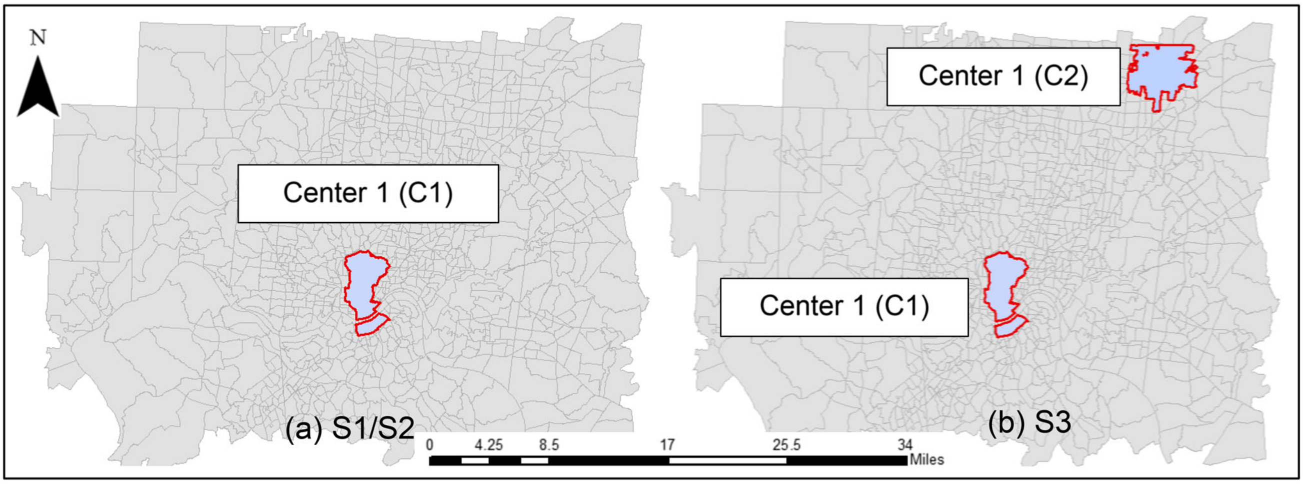


Fig. 4 Incentive boundary of each assumed scenario in the case study

locate within the center area. Similar to S2, the mixed-use center schema is adopted in S3, but two different centers are planned.

The following steps are involved in developing a regional-level scenario. First, the incentive boundaries need to be determined to define the boundaries of the future centers in the study area. In S1 and S2, a single center—Center 1 (C1) is developed in the traditional downtown area. In S3, two centers are developed—C1 and Center 2 (C2) which is located in Mason and West Chester areas. Figure 4 illustrates the locations of C1 and C2. Table 1 enlists assumed changes of the population, employment, and school enrollment in the incentive area and non-incentive area. The incentive area is the area where the future development is planned to satisfy the addressed demand. The non-incentive area refers to the areas outside the defined incentive boundaries.

Figures 5 and 6 present projected population and employment changes in each scenario compared with the background data. The population and employment growth rates in the affected TAZs are assumed to remain static. Population/employment growth rate is calculated as the ratio of the total number of increased population/employment to the total number of population/employment of the baseline. In S1, the increased population is widely distributed in the study area, and majority of increased employment are located in the defined center C1. S2 adopts the same employment project schema as S1, but S2 develops a mixed-use center and allocates most of the increased population in the C1 area. S3 develops two centers C1 and C2 with the mixed-use development strategy.

With the projected land use under the given changes in population and employment, some statistics of land use characteristics in terms of land use density, diversity, and design are calculated for S1, S2, and S3 (listed in Table 2). Results indicate that S1 and S2 have the same high employment density in C1. The major difference between S1 and S2 is that S2 has a much higher population density in the C1. Compared with S2, S3 has two centers developed. Unlike S1 and S2, in S3 the majority of the increased population and employment are allocated into two centers, i.e., C1 and C2, rather than one center only. In S1, C1 has a high job/population ratio of 1.563. That is much higher than the average ratio 0.502 of the entire study area and could results in longer commuting distances. In S2 and S3, the job-population ratio is 0.636 and 0.726, respectively. The job-population ratio of C2 is 0.262 in S2 and 0.427 in S3. With respect to the job mix, in S3, the C2 has a higher degree of mix of jobs, which obtains a value of 0.482 and is increased by 0.171 compared to that in S1 and S2. For the accessibility, it can be concluded that the high-density, and well-mixed land use pattern provides an improved accessibility for travelers to destinations, such as C1 in S2 (with

Table 1 Assumed changes in land use for each scenario

Scenarios	Growth within the center(s)			Growth outside the center(s)		
	POP (%)	EMP (%)	SCENROLL (%)	POP (%)	EMP (%)	SCENROLL (%)
S1	2	13	2	13	2	13
S2	13	13	13	2	2	2
S3	13	13	13	2	2	2

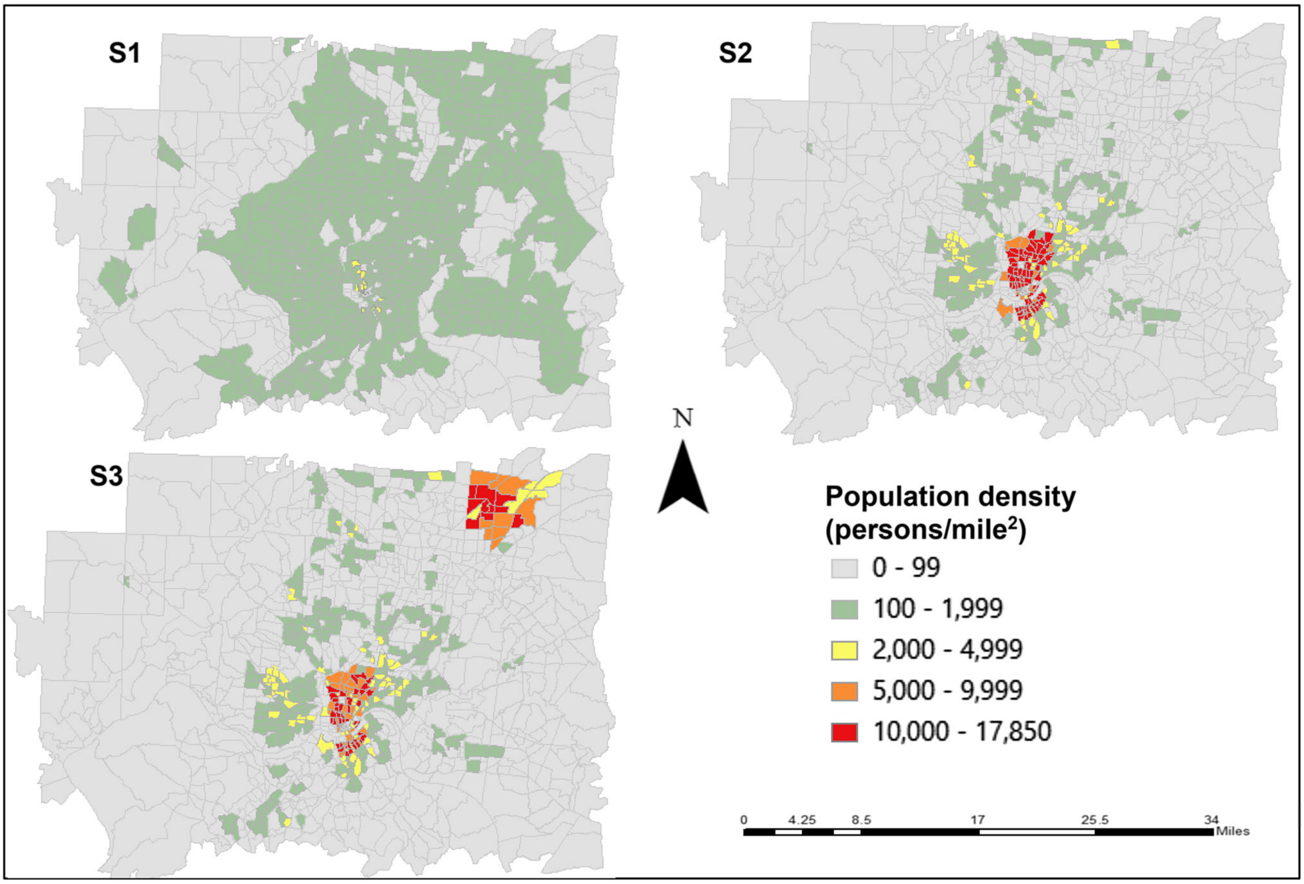


Fig. 5 Projected changes in population density compared with baseline data

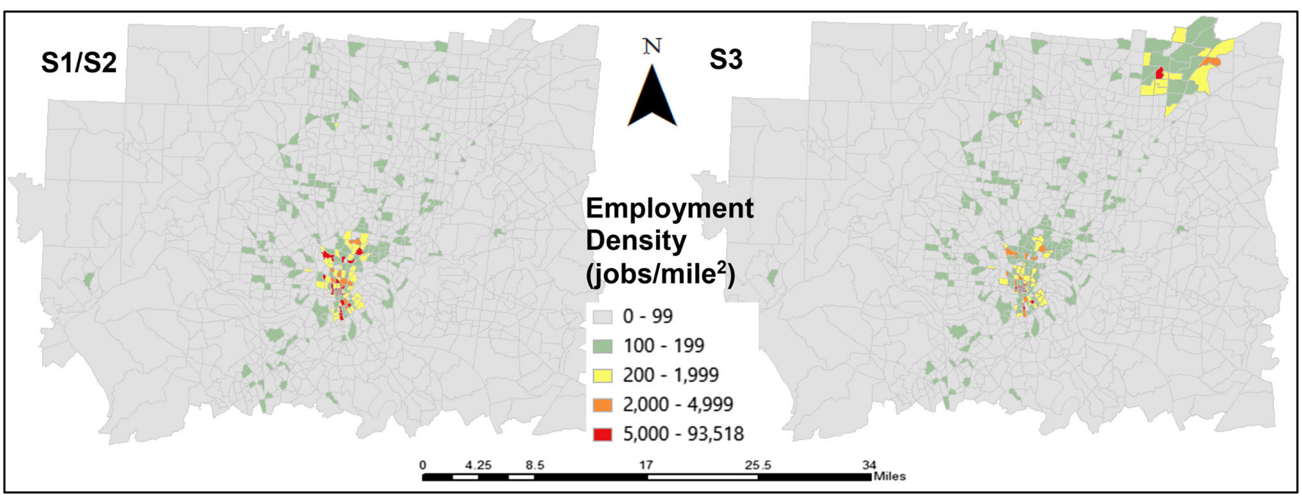


Fig. 6 Projected changes in employment density compare with baseline data

a value of 0.825), and C2 in S3 (with a value of 0.671). According to the discussion in the previous section, the high-density, mixed-use, and easier-accessible land use development tends to reduce travel distance, thus reduces total vehicle miles travelled, and consequential vehicle CO_2 emission and fuel consumption.

3.2 Result Analysis of Running Activity-Based TDF Modeling with Local Data

The activity-based TDF model is developed following the structures as discussed in methodology section and calibrated using the 2009–2010 household travel survey data

Table 2 Statistics of land use patterns for each scenario

Land use variables	Subareas by scenario								
	S1			S2			S3		
	C1	C2	Other	C1	C2	Other	C1	C2	Other
Density[a]	16,026	2747	1902	25,139	2495	1751	17,263	10,119	1751
Job-population	1.563	0.262	0.426	0.636	0.262	0.480	0.726	0.427	0.480
Job mix	0.672	0.311	0.411	0.672	0.311	0.411	0.563	0.482	0.411
Accessibility	0.791	0.317	0.524	0.852	0.317	0.524	0.821	0.671	0.524

[a] The unit of the density is (persons + jobs)/mile^2

Table 3 Number of trips, average trip length, and percentage of intra-center trips

Scenarios	Trips	Average trip length (mile)	Percentage of intra-center trip (%)	
			C1	C2
S1	5.9023×10^6	5.56	7.91	0.87
S2	5.9065×10^6	5.14	12.19	0.78
S3	5.9067×10^6	5.13	7.66	4.78

Table 4 Comparison of scenario costs

Scenario	Travel time cost (10^3 \$)	Fuel consumption cost (10^3 \$)	Carbon cost (10^3 \$)	Travel operation cost (10^3 \$)
S1	17,832	3988	702	22,522
S2	14,498	3691	660	18,849
S3	13,446	3683	637	17,766

[47] and traffic data at typical permanent traffic monitoring stations at major highways in the Cincinnati area. Since that activity pattern choice behaviors are different among workers, students, and others, the activity pattern utility function is then calibrated separately for these three categorized users. Tables 3 and 4 show the calibrated models for activity pattern unity, destination choice, and mode choice for categorized users and modes with difference trip purposes. As a result of running the TDF model, the total number of trips, percentage of intra-center trip, and average trip length of each scenario are summarized in Table 3. A intra-center trip is referred to a trip with both origin and destination located within the same center. S1 is developed with one single-use center, while S2 and S3 are developed with denser and mixed-use center(s). With the mixed and multi-center development, the number of trips increases slightly. Since the mixed-use, compact development can bring closer origins and destinations, the average travel distances are shorter in S2 and S3 than that in S1. The multi-center development strategy in S3 produces shortest average trip length. In the wake of the increasing of land use intensity and diversity, more intra-center trips are generated in each center of S3.

Figure 7a visualizes VMT and VHT by scenario. Compared with S1, there are 7.39 and 18.74% decrease in VMT and VHT, respectively, in S2, and 7.58 and 24.68%

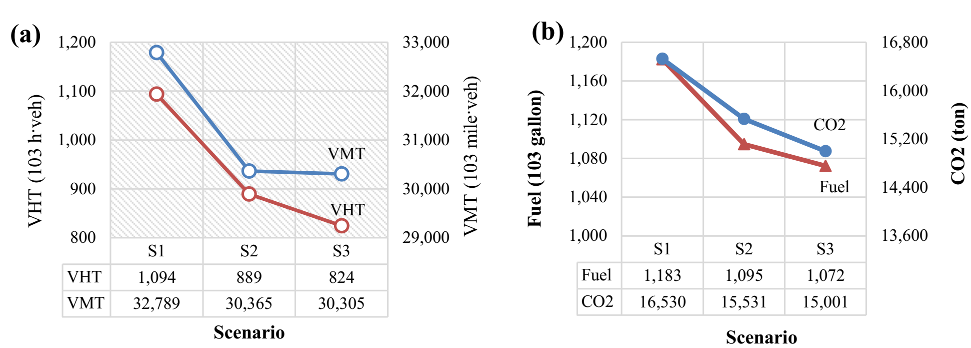


Fig. 7 **a** VMT and VHT by scenario; **b** fuel consumption and CO_2 emission by scenario

decrease in VMT and VHT, respectively, in S3. While the number of trips increases slightly in S2 and S3, the overall trip length is reduced as a result of the compact land use development. In other words, the increasing of the trip number is not big enough to offset the reduction of VMT and VHT as a result of the reduced trip distances.

Figure 7b visualizes the values of CO_2 emission and fuel consumption of each scenario. Compared with S1, there is a reduction of 7.44 and 9.33% in CO_2 in S2 and S3 accordingly. The shorter travel distance in S2 compared with S1 results in a salient fuel consumption reduction. There is a 6.04 and 9.25% of fuel consumption reduction in S2 and S3, respectively, compared with S1.

Table 4 demonstrates the cost-related estimation results for scenarios S1, S2, and S3 with the list of travel time cost, fuel consumption cost, carbon cost, and total travel operation cost. Compared with S1, S2, and S3 achieve a 16.31 and 21.11% reduction in the travel operation cost, respectively. The results show that mixed-use, compact development patterns produce less cost than the single-used, sprawl development pattern. Furthermore, the multi-center development strategy can help to reduce the travel operation cost compared with the single-center scenario.

4 Summary and Conclusion

The methodology involved in the development of the integrated system is reflective of a scientific approach and synthetic analysis system to facilitate the exploration and disclosure of the cause-and-effect mechanism between the land use or relevant planning with projected socioeconomic changes, and their impact on transportation operation and carbon emission. The activity-based model has been adapted into the regional-level transportation emission analysis. The scenario development function in the system is designed to provide the functionality for addressing "what-if" transportation emission impacts pertinent to traffic situations that are forecasted from affected future land use changes. This method has been viewed by far as the best way to deal with uncertainty related to decision-making factors for future forecasts that cannot be predicted from modeling. A case study is conducted to demonstrate the functionality and application of the integrated system in the Great Cincinnati area. In the case study, the impact of land use pattern on travel demand and vehicle emissions is examined. Compared with single-use development, the mixed land use pattern is capable of reducing the total vehicle travel, CO_2 emissions, and fuel consumption. Meanwhile, the multi-center based compact development can bring closer origins and destinations. As the consequence, less VMT and VHT, vehicle CO_2 emissions and fuel consumption could be resulted. The case study results indicate that such an integration approach can facilitate the process of assessing land use planning alternatives with respect to not only travel demand impact, but also traffic-source emission based sustainability.

This synthetic computing platform will be ultimately developed to facilitate the scenario-based quantitative analysis of cause-and-effect mechanisms between land use changes and/or traffic management and control strategies, their impacts on traffic mobility and the environment. For example, with the integrated system, a set of "what-if" analyses can be performed to evaluate transportation system performances with the promotion of transit system, increased investment in bicycle facilities, and improvement of community walkability. The measured performances can help planners and policy-makers to assess strategies and/or policies for improved transportation mobility and sustainability. The application of this functionality will be presented in other publications in the future.

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