Modeling Land Use Changes, Sustainable Water Management and GHG Benefits

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Narrative

Project Background:

Achieving our climate goals requires more than cap and trade, renewable and low carbon fuels. We must also pursue carbon-smart land use and transportation policies. Tools to predict and measure the outcomes of these policies are essential to achieving our greenhouse gas reduction targets.

We must be able to analyze urban scenarios and quantify the carbon balance. Similarly, knowing the co-benefits from carbon reductions for water, natural habitat, infrastructure financing, service costs, energy use, public health are important to the interconnected policy environment – pointing the way to smart land use and transportation policies where they may not be apparent otherwise.

UrbanFootprint provides a strong framework for analyzing the range of impacts from land use and transportation scenarios. With additional work to refine its capability in estimating carbon impacts, it becomes a cost-effective greenhouse gas emissions assessment tool supporting cap-and-trade policies in California.

Phase 1 convened a technical committee to review and advise on model enhancements and enhances critical policy and modeling components of UrbanFootprint. This phase resulted in improvements in and verification of UrbanFootprint’s sensitivity to policies on water use, building energy efficiency, and regional transportation policy and began the enhancement of the model’s transport modeling capabilities to reflect transportation demand management (TDM) and related strategies.

Phase 1 was comprised of three tasks shared among a set of four collaborating organizations, the Urban Land Use and Transportation Center (ULTRANS), within the Institute of Transportation Studies, UC Davis, Calthorpe Associates, Policy In Motion, and Fehr & Peers. Fehr & Peers participated as a subcontractor to ULTRANS.

Task 1. Convene a Technical Advisory Committee (TAC) to review UrbanFootprint’s current inputs and methods, and recommend and evaluate improvements.

Task2. Policy enhancements: Implement improvements to the underlying input parameters and analytical methods for water use analysis (quantity and cost), water-energy connections, building energy use, energy generation, vehicle efficiency and vehicle fleet mix, and the fiscal and environmental effects of policy and technology changes, with specific attention being paid to greenhouse gas emissions.

Task3. Transportation Modeling Enhancements: The travel model components of UrbanFootprint are to receive additional review, documentation, and we will identify critical improvements for cap-and-trade and related analyses. Basic improvements to the travel modeling tools will be made to support demand management in the existing modeling framework. Fehr & Peers under subcontract to ULTRANS lead this segment of the project. Improvements beyond the demand management support were not scoped for phase 1.

Additionally, at the request of Resources Legacy Fund project management, we provided support to Calthorpe Associates and a coalition of interested NGOs in performing analysis for Sustainable Community Strategies for the San Joaquin Valley.

Results and Outcomes:

The original intent had been to use the Tasks in Phase 1 as building blocks to support the transition of the model to the University of California as an open source platform. This process has been delayed at the State with no final decision on a location to house the model being made so far though UC Davis either alone, or in collaboration with other parties. Regardless, work preparing ULTRANS to support future deployments of UrbanFootprint continues and we remain active and involved in the field.

Technical Advisory Committees:

The two technical advisory committee (TAC) meetings were well received and well attended.

In particular the first TAC meeting was attended by twenty nine people in person and an additional five by conference line. The attendees represented a wide range of governmental agencies at the state and regional level as well as representatives of private industry and universities. Most of the invitees were already familiar with the basic premise of UrbanFootprint allowing us to dive deeper into a discussion the underlying methods than had previously been done with a group of this size and breadth of knowledge.

The TAC identified several areas targeted for specific improvements within the scope of this project. Generally these included a review and when warranted a refactoring of model parameters. In particular the parameters that relate to the efficiency of water and energy use by climate zone are focuses for review and updating. The TAC identified several new sources of data that were not previously used and some areas where the model structure limited its flexibility for policy analysis. It also made several recommendations for continued improvements to the model that of necessity must be postponed pending future funding.

The first TAC was a full day event with a catered lunch hosted at the Hyatt Place on campus at the University of California, Davis.

The second TAC occurred in the conference room at the new zero net energy West Village offices of the Institute of Transportation Studies (ITS), the parent organization of ULTRANS. The TAC meeting was attended by eighteen members with several more briefed independently either before or after the primary TAC meeting. The updates and improvements were reviewed with the TAC and questions either answered or collected for follow up. The most significant remaining issues were questions on the appropriateness of building energy inputs, the water-energy use connection, and the appropriate scope of some transportation analyses.

Appendix 1 contains a list of attendees at each of the TAC meetings.

Building Inventory Model:

One of the items suggested by the TAC was the direct inclusion of a building inventory model into UrbanFootprint. This will enable more dynamic modeling and analysis of policy and technology scenarios.

The new building inventory model produces scenario-based counts of residential units and commercial floor space distinguished by building type, location, status (new, renovated/replaced, or unchanged), vintage (year built, for new buildings only) and types of retrofitting applied for each year between the base and horizon years in the model. This scenario output not only forms the basis for energy and water impacts analysis in UrbanFootprint, but can serve as an input for more detailed energy and water analysis in other platforms.

Significantly, the model goes beyond a simple accounting of existing development and planned growth. The building inventory is subject to user-specified rates for building upgrades over time. Building upgrades include renovations/replacements and retrofits, which can replicate either incremental improvements or the installation of specific technologies such as on-site renewables generation or the installation of solar hot water heating systems. The model has been designed to allow for flexibility in defining upgrade assumptions (or rates of adoption of specific technologies) and their associated energy and water demand reductions. Energy and water savings can be associated with upgrade types such that users can test the impacts of specific policies additively or in isolation.

Interactions between retrofits such as energy savings generated by reductions in water use may be approximated, but not explicitly calculated because of the proportional and independent manner in which retrofits are applied to the population of units.

For additional information please see the attached technical documentation in appendix 2.

Fleet Mix Model:

Similarly to the Building Inventory Model, the TAC recommended finding ways decouple assumptions about the fleet mix, its efficiency and the consequences of policy and technology options.

A flexible framework for formulating passenger vehicle fleet mix scenarios has been created to enhance the ability of UrbanFootprint to estimate transportation-related GHG emissions into the future. Assumptions about new vehicle performance, market share of different vehicle types, and vehicle retirement rates are loaded into this model to determine the aggregate fuel and energy efficiency of the on-road fleet in any year. When combined with an estimate of vehicle miles traveled (VMT), and applying the assumption that each vehicle is driven equally, we may calculate fuel and energy demand, and resulting GHG emissions.

From a technical standpoint, the newly developed fleet mix model, coded in Python, bears many structural similarities to the building inventory model. An initial base fleet is defined as the total number of vehicles on the road proportioned by type. This initial fleet is subject to differential retirement rates, by vehicle type, of these vehicles from active use. Vehicles that retire from the base fleet are either not replaced, in the case of net decreases in vehicles, or become part of a pool with net fleet growth, and subsequent retirement from the new vehicle fleet, that is distributed into new vehicles based on an assumed mix of vehicles sold in each year.

For additional information please see the attached technical documentation in Appendix 2.

Travel Model Enhancements:

Fehr & Peers under subcontract to ULTRANS assisted Calthorpe Associates in implementing a travel demand management component to the existing transportation analysis toolkit. These included the addition of pricing policies for vehicle operations and fuel costs, parking prices, improvements to transit services, and employer trip reduction programs. The existing model now has basic methods for evaluating road congestion effects. Fehr & Peers outlined additional improvements to address commercial vehicles, integration with the activity-based travel demand models that are becoming the standard in larger MPOs and some smaller ones, a network based analysis of travel (too enhance or replace the current aggregate measures), transit level-of-service, and interregional travel and goods movement.

Details are provided in the appendix 3.

Water-Energy Relationship:

Dr. Edward Spang, of UC Davis's Center for Water-Energy Efficiency outlined the potential of water and energy efficiency improvements to impact total energy use in the State of California. The first pathway is increased energy efficiency in appliances using water, and the second is improved efficiency in water usage which creates a feedback loop with energy efficiency improvements resulting in substantial reductions in total energy use. The new building inventory and energy use toolkit can implement the first fully, and can approximate the second pathway. For full details on Dr. Spang's proposed integration of water-energy feedbacks please see the included appendix 4.

Residential Energy Usage:

Dr. Giovanni Circella, ULTRANS, estimated an alternate formulation of residential building energy usage that included both electricity and natural gas. After obtaining the full Residential Appliance Saturation Survey (RASS) dataset from the California Energy Commission, exploratory analysis was conducted. This analysis determined that though the RASS dataset is a promising source of information for updating the energy baselines, it is not without significant limitations. In particular, information derived from it for areas of extreme climactic values in California and less common building types (townhouses and apartments/condos) cannot be modeled robustly due to the small sample sizes. As a result, energy consumption modeled for these areas should be regarded as quite uncertain.

The final estimated statistical model for energy consumption predicts energy consumption based on unit type (single family, townhouse, and apartment), size in square feet, and heating and cooling degree days. This formulation should be implementable in multiple forms either using actual heating and cooling degree days, or average values by climate zone. Additionally, this formulation should allow for estimates of energy use changes due to climate change.

For additional information please see appendix 5.

San Joaquin Valley SCS Support:

ULTRANS also provided support to a coalition of NGOs conducting analysis of the San Joaquin Valley MPOs' progress on their Sustainable Community Strategies. This support was at the request of the Resources Legacy Fund. ULTRANS provides summaries of land use change based on the analysis of historical land use change data and other existing land use data libraries developed at the Information Center for the Environment, Department of Environmental Science & Policy, UC Davis, which shares computing and staff resources with ULTRANS. ULTRANS also further developed methods used for exporting baseline travel information from ULTRANS's state of the art activity-based travel model for use by UrbanFootprint.

RESOURCES LEGACY FUND

RESOURCES LEGACY FUND FOUNDATION

Project Outcomes Report

Organization: ULTRANS, UC Davis **Project Name:** Modeling Land Use Changes, Sustainable Water Management and GHG Benefits
Grant #: 2012-0345

Grant Period Covered by Report: October 29, 2012 – May 31, 2013 **Project Outcomes Prepared By:** Nathaniel Roth, PI

Project Goal(s):

1. Establish and conduct a technical review process for the water, energy, and transportation components of UrbanFootprint. This review process will include an evaluation of the current inputs and methods for analyzing the water use, energy use, connections between them and the transportation needs of scenarios including, where possible, the fiscal and environmental impacts of policy and technology changes.
2. Enhance the input data and analytical modules addressing water use and cost.
3. Enhance the input data and analytical modules addressing the water-energy relationship.
4. Enhance the input data and analytical modules addressing building energy use.
5. Enhance the input data and analytical modules addressing energy generation and resulting pollutant and GHG emissions.
6. Enhance the input data and analytical modules addressing mobile source emissions and related policies (vehicle efficiency, fuel use, and emissions).
7. Improve the transportation modeling capabilities through the addition of demand management analysis.
8. Document a plan for long range improvements to the transportation modeling framework.

Category and Objective	Progress/Process *(description of work to-date)*	Conservation Outcomes *
Task 1: Technical Advisory Committee(s)	Two technical advisory meetings were conducted. The first on November 28, 2012, attended by X attendees, at the Hyatt Place, UC Davis, was a full day event including lunch and snacks, and followed by a policy meeting with representatives of state and regional agencies as well as university and NGO representatives. The second hosted at the West Village offices of the Institute of Transportation Studies on the afternoon of March 13th, 2013 was project summarization, review, and update briefing. It was attended by X people. The attendee lists for each meeting are included as appendices.	The technical advisory committee provided recommendations to the overall team on methodological and theoretical considerations for modeling complex urban systems of energy, water and transportation during the first technical advisory meeting. At the second advisory meeting improvements to the methods in use by UrbanFootprint were reviewed.
Task 2: Policy Enhancements		

2a: Water Use and Cost	Updates to the water use and cost components of UrbanFootprint's water and energy models were made based on feedback from technical advisory committee members and other subject matter experts	These updated input values and methods better represent the water demand and costs than the preliminary values and models in use at the beginning of the project.
2b: Water Energy and Greenhouse Gas Emissions	Improved linkages between water and energy use have been implemented for UrbanFootprint.	The updated methods will allow UrbanFootprint users to evaluate the effects of feedback loops between water use and energy demand with linkages to GHG emission calculations
2c: Building Energy Use, Cost, and Greenhouse Gas Emissions	The building energy use and cost values were improved based on feedback from the TAC. Additionally the building inventory module was updated to be a Python based toolset that could be directly integrated into UrbanFootprint.	The updated parameters for building energy use and costs will benefit the model through improving its sensitivity to changing policy and technology. The improved building inventory model will allow for more detailed tracking of building inventories through time, and more detailed analysis of policy and technology based changes in building energy use.
2d: Energy Generation and Related Greenhouse Gas Emissions	Based on review with the technical advisory committee updates and improved parameters were derived for energy generation and resulting GHG emissions.	Building off of the improvements to water related energy consumption, and building energy consumption cumulative effects on energy generation demand

		and the resulting GHG emissions can be examined in greater detail.
2e: Vehicle Efficiency, Fleet Mix, Fuel Use, Fuel Mix, and Emissions	The existing MS Excel based fleet mix module was updated to a Python module for direct integration with UrbanFootprint. Based on TAC feedback, the emphasis was on making the toolkit flexible to easily adapt to alternate policy and technology/efficiency scenarios.	The improved fleet mix model and related impact evaluation tools will allow for a more detailed analysis of fleet mix effects on criteria pollutant, GHG, operations and maintenance costs, and demand.
Task 3: Transportation Modeling Improvements	Fehr & Peers under sub-contract to ULRANS provided direct support to Calthorpe Associates in adding basic travel demand management capabilities to the UrbanFootprint platform. Fehr & Peers also outlined a path for future improvements to the travel analysis platform suitable for use in seeking ongoing funding for improvements.	Demand management may be one of the more effective methods for managing mobile source GHG emissions and fuel use. UrbanFootprint now has basic support for analyzing demand management techniques. Additionally, there is now a guiding document that can be used to guide the search for future funding to continue improvements to the travel modeling capabilities in UrbanFootprint.

Lessons Learned:

Overall, this project has indicated that the UrbanFootprint application is on a good path forward. None of the responses from the technical advisory committee indicated that UrbanFootprint was not worth additional investment in improving. In fact, many of the committee members emphasized that there was a great deal of potential in UrbanFootprint to be a transformative tool for the creation, visualization, and analysis of land use scenarios in California, and that the funding currently available would only make a start on enabling the many potential uses for UrbanFootprint in public, private, and NGO practice.

The techniques for handling development of modules for UrbanFootprint will be valuable in the future as new modules or improvements to existing ones are developed and integrated into UrbanFootprint. Additionally, some of the methods demonstrated in the fleet mix and building inventory improvements may allow for faster impact assessment allowing policy evaluation in near "real time" as scenarios are created and modified.

Additional Materials

Appendix 1: Technical Advisory Committee Meeting Attendees:

November 28, 2012:

In Person:

- Joe Caves, Conservation Strategy Group
- Sandy Spelliscy, Resources Legacy Fund
- Rich Juricich, Dept of Water Resources
- Raef Porter, SACOG
- Audrey Lee, CPUC
- Doug Ito, CARB
- Chad Baker, Caltrans
- Bill Mosby, Caltrans
- Giovanni Circella, UC Davis
- Jin Qiu, ARB
- Edward Spang, Center for Water-Energy Efficiency, UC Davis
- Susan Handy, UC Davis
- Chris Ganson, OPR
- Mike McCoy, Strategic Growth Council
- Louise Bedsworth, OPR
- Martha Brook, CEC
- John Taylor, ARB
- Nesamani Kalandiyur, ARB
- Guoxiong Huang, SCAG
- Gordon Garry, SACOG
- Bob Johnston, UC Davis
- Jerry Walters, Fehr and Peers
- Nate Roth, UC Davis
- Lauren Michele, Policy in Motion
- Tristan Osborn, Cobblestone Placemaking
- Joe DiStefano, Calthorpe Associates
- Garlynn Woodsong, Calthorpe Associates
- Nick Wilson, Calthorpe Associates
- Erika Lew, Calthorpe Associates

Via phone:

- Kathy Freas, CH2M Hill
- Clint Daniels, SANDAG
- Ian MacMillan, South Coast AQMD
- Robert Cervero, UC Berkeley
- Aaron Katzenstein, South Coast AQMD

March 13, 2013:

- Gordon Garry, SACOG
- Chris Ganso, OPR
- Rich Juricich, DWR
- Doug Ito, CARB
- Edward Spang, Center for Water-Energy Efficiency, UC Davis
- Jonathan Taylor, CARB
- Jin Qui, CARB
- Sandy Spelliscy, RLF
- Chad Baker, Caltrans
- Michael McCoy, Strategic Growth Council
- Cordel Stillman, Sonoma County Water Agency
- Joe Caves, Conservation Strategy Group
- Lauren Michele, Policy in Motion
- Joe DiStefano, Calthorpe Associates
- Erika Lew, Calthorpe Associates
- Nick Wilson, Calthorpe Associates
- Jerry Walters, Fehr & Peers
- Nathaniel Roth, ULTRANS, UC Davis

Appendix 2: UrbanFootprint Technical Documentation for the Building and Fleet Mix Enhancements

Background:

In UrbanFootprint 1.0 both the Building Inventory and Fleet Mix components of the model were handled through the use of MS. Excel Spreadsheets. In order to change policy scenarios related to these two items, adjustments needed to be made in the spreadsheets, the changes saved, and then the model be run. This has proven to be a workable, but somewhat inflexible solution to the challenge.

The building inventory and fleet mix models were created to remove the dependency on the spreadsheets and to enable a more fluid scenario testing environment for changes in assumed building and vehicle efficiency and replacement (or retrofit) rates.

The models described below are available to UrbanFootprint and are licensed under the GPL for any use. Like all models of this type, they are likely to undergo further enhancement over time.

Building Inventory Model:

The Basics:

The new building inventory model produces scenario-based counts of residential units and commercial floorspace distinguished by building type, location, status (new, renovated/replaced, or unchanged), vintage (year built, for new buildings only) and types of retrofitting applied for each year between the base and horizon years in the model. This scenario output not only forms the basis for energy and water impacts analysis in UrbanFootprint, but can serve as an input for more detailed energy and water analysis in other platforms.

Significantly, the model goes beyond a simple accounting of existing development and planned growth. The building inventory is subject to user-specified rates for building upgrades over time. Building upgrades include renovations/replacements and retrofit, which can replicate either incremental improvements or the installation of specific technologies, such as on-site renewables generation or the installation of solar hot water heating systems. The model has been designed to allow for flexibility in defining upgrade assumptions (or rates of adoption of specific technologies) and their associated energy and water demand reductions. Energy and water savings can be associated with upgrade types such that users can test the impacts of specific policies additively, or in isolation. Notably, the retrofit structure creates flexibility in transferring consumption from one energy source to another, or creating relationships between reductions in two or more measures.

Interactions between retrofits such as energy savings generated by reductions in water use may be approximated, but not explicitly calculated because of the proportional and independent manner in which retrofits are applied to the population of units. Explicitly tracking the number, type, and vintage of retrofits applied to each building unit, enabling direct calculation of these values is possible, but an implementation of this method would create longer run times than is viable for a sketch model intended for use in a public venue.

The ability to generate a building inventory for any year of a scenario is a new advancement. The building inventory model generates interim-year totals using base-year and end-year scenario totals for new growth and changes to existing development. **Table 1** provides a simple sample of the building inventory output.

Table 1. Sample building inventory output for a single building unit type. In this example, the total housing stock grows by 1000 units per year while the base inventory retires 5 percent of the remaining base inventory each year. Both the replacement and new unit inventories replace 2 percent of the existing stock each year, with the most recent 3 years being excluded from this replacement.

Year	Total Housing Units	Remaining Base Inventory	Total Replacement Units	Total New Units	Year of Unit Manufacture	Replacement Units by Year of Manufacture	New Units by Year of Manufacture
2010	100,000	100,000	-	-	N/A	-	-
2011	101,000	95,000	5,000	1,000	2011	5,000	1,000
2012	102,000	90,250	9,750	2,000	2011	5,000	1,000
					2012	4,750	1,000
2013	103,000	85,738	14,263	3,000	2011	5,000	1,000
					2012	4,750	1,000
					2013	4,513	1,000
2014	104,000	81,451	18,549	4,000	2011	4,900	980
					2012	4,750	1,000
					2013	4,513	1,000
					2014	4,387	1,020
2015	105,000	77,378	22,622	5,000	2011	4,802	960
					2012	4,655	980
					2013	4,513	1,000
					2014	4,387	1,020
					2015	4,266	1,040
2016	106,000	73,509	26,491	6,000	2011	4,706	941
					2012	4,562	960
					2013	4,422	980
					2014	4,387	1,020
					2015	4,266	1,040
					2016	4,148	1,059

The model currently generates inventory data based on aggregated scenario totals at broader geographic scales (city, region, or climate zone). Working at smaller scales (such as the parcel or grid-cell scale) would likely introduce false locational precision with respect to broadly defined assumptions about future change (for example, gradual rates of building replacement over time); it would also be computationally intensive. Because the building inventory totals are generated at aggregate scales, the interim-year totals represent stops along a linear path from a base to an end-year scenario, rather than unique scenarios in themselves. Upgrades to represent defensible, parcel or grid cell specific building change will require significant advancement and the inclusion of a predictive modeling component. This could take many forms from simple (such as an adaptation of UPlan's algorithms) to complex microsimulation of developer actions.

The building inventory model is coded in Python, and will be linked to the user interface of UrbanFootprint. The model code is written to be flexible, with run times measured in seconds such that it could be run easily within a live public outreach session. With simple modifications, the building inventory and energy use model could be portable to other applications.

Technical Description:

The building inventory model is coded in Python, written to be flexible and have run times measured in seconds that would allow its easy use within a live public outreach session and will be linked to the user interface of UrbanFootprint. With simple modifications, the building inventory and energy use model cold be portable to other applications. The model includes four basic steps:

1. Load data and policy assumptions from the UrbanFootprint Core
2. Calculate building mix by year and cumulative rates of retrofit by type.
3. Application of building efficiency rates and retrofits to generate summaries of criteria measurements, currently electricity, natural gas, and water, though that list is expandable.
4. Writing results to database.

In the data loading step, the net change by building type in a geographic area, referred to as a "Geoid," is calculated and handed to the building mix model. A Geoid may be defined flexibly, but is intended to provide localization of the land use change at a scale that can represent significant differences in climate zone or policy environment. The net change by building type is preprocessed to provide the incremental change in number of units by type each year. Units may be either residential units or commercial square feet.

Given the number of units by type in the initial year, referred to as the base inventory, the net change in units by type is either added to the total number of units, with a record of how many units were created in each year (added to the new unit inventory), or removed from the base inventory or replacement unit inventory proportionally to the number of units by type and age. The replacement inventory is populated through the assumption that some proportion of the standing units will be replaced or sufficiently rehabilitated that they take on efficiency properties in line with those of a newly constructed unit of the same type on an annual basis. All three inventories are subject to replacement, with the built in ability to protect recently constructed units in the replacement and new unit inventories from immediate replacement for a customizable number of years.

This process results in us knowing for each year, how many units of each type remain from the base inventory, and for the new and replacement unit inventories we know, for each year, how many units of each type were created in each preceding year.

Depending on system load, and number of years being analyzed, the building mix calculation can take less than a quarter second per Geoid. Because each Geoid is effectively independent in the calculation this process is eligible for parallelization though this will require additional coding to fully implement.

Retrofits are applied to each of these unit totals by formula. The effective rate of retrofit for each group of units is portrayed in Equation 1.

$$r_e = 1 - (1 - r)^n \qquad \text{Equation 1}$$

Where:

r = the annual rate of retrofit for the unit type and retrofit type

n = the number of years the unit has been in existence (or in the model for base inventory)

r_e *= the effective rate based on the number of elapsed years*

The energy and water impacts of the building mix are tracked through impacts that are called “measures” within the model. The list of “measures” is customizable, but the current set is, electricity, natural gas, and water.

Each unit has a baseline usage of each measure. In the base inventory units, this baseline is adjusted by an annual rate of improvement. For the new and replacement unit inventories this is adjusted by both an annual improvement in the baseline usage, indicating the initial efficiency of the unit as it is built, and then by an annual rate of improvement from that baseline.

A retrofit applies a percentage discount to the total of each measure “consumed” by each unit. For each unit type and age, the usage of each measure is calculated as the difference between the number of units times the applicable rate of usage (without retrofits), and the sum of all discounts which are calculated as the total number of units times the effective retrofit rate times the baseline usage times the percent discount (Equation 2).

$$Net\ Usage = U * N - rU * N * R_r * D_r \qquad \text{Equation 2}$$

Where:

U = Baseline usage for a selected measure, by unit age, type, and year of construction

N = Total number of units by type, age, and year of construction

r = Retrofit type

R_r = Effective retrofit rate for retrofit type r

D_r = Discount for the measure in retrofit type r

The baseline usage (*U * N)* is recorded for each category as is the effective discount for each retrofit to each measure and is accessible by querying the output dataset.

The retrofit structure creates flexibility in transferring consumption from one energy source to another, or creating relationships between reductions in two or more measures. It can also be used to assign per unit (residential) or per square foot adoption rates of improvements such as greywater use or PV solar installation.

Programming Notes:

The Building Mix tool set is constructed as a set of Python classes that provide the needed functionality to run the building mix and usage analysis. Each class fills a specific role and is a largely self-contained unit for accomplishing its designed tasks.

These classes are:

MakeTables:

MakeTables creates the needed tables within the underlying PostgreSQL database to store the inputs and outputs of the building inventory model. This class should only need to be used once as the tables are not created or destroyed (dropped) by the subsequent model components. In the future this class will be replaced for UrbanFootprint’s use by a Django models.py

LoadTables:

LoadTables imports a set of comma separated value (csv) tables into the database to populate initial parameters for building initial inventory, growth, efficiency, turnover, retrofit, and replacement rates.

Interpolate:

The interpolate class provides a calculator that takes two values for two known years (eg. 2010 and 2020) and provides values for each intervening year based on an assumed linear change between the two known years.

ExpandTables:
ExpandTables generates expansions of input data to represent the extrapolation of trends represented in the input years into annual factors where needed. This automates the interpolate option across all needed variables.

BuildingMix:
BuildingMix is the central component of the model. It loads all needed inputs from either the database tables, or when run in a testing mode from direct inputs, and executes the building mix methods on all building types, over all years between the specified start and end years. Results are recorded into the database.

Some Terminology:

Scenarios (sid)

The BuildingMix model is setup to allow flexibility in analyzing different policy scenarios or geographic areas. Each configuration of the building mix module is considered to be a scenario and is assigned a Scenario ID (sid) and a user defined scenario name. A scenario is a complete set of configuration information that includes all inputs, settings, and outputs.

Geoid

Scenarios also include geographic sub areas (or geoids). These exist to provide support for tracking differences in climate zone, or selected subareas for analysis. If there is only one climate zone, and no subareas are highlighted for analysis then the entire region may be considered a single geoid.

Scenarios may be copied and updated with new data or policy settings to create new scenarios.

Unit Type

A unit type is an identifier for a type of building unit. What constitutes a unit is left intentionally abstract so that it can be used either for an individual housing unit, or a square foot of non-residential space.

Growth

The number of net new units of each unit type created in each year. These become truly new units in the building inventory.

Base Inventory

The number of original units remaining in any year

Replacement Inventory

The number of units that are replacements for base inventory units, but are of the same type. In general these are units that are either torn down and rebuilt from scratch, or are renovated so heavily that they are assumed to take on the properties of a new unit built in that year.

New Inventory

These are units that result from net growth in the total number of units in a type. These units may be replaced, but replacements of these will be counted as new units not replacement.

Replacement Rate

The annual rate at which a unit is replaced by a newly constructed unit of the same type. There are independent replacement rates for base and newly constructed units of each unit type.

Lag

Newly constructed units may be protected from replacement for a period of time. This length of time is the lag.

Measure

A measure is the thing being evaluated for usage by each unit. For example "water" would likely be a measure that would be applied to a unit identifying how much water a unit consumes.

Baseline Usage

The amount of each measure used by a single unit of each unit type if the unit were built in the base year.

Baseline Annual Efficiency Improvement

The rate of improvement over the base year energy efficiency that a new unit (new or replacement) has when constructed.

Annual Efficiency Improvement

The rate by which the baseline usage for a unit improves (or disimproves) on an annual basis. For a base unit, this is measured from the base year. For newly constructed units (new or replacement) this is an improvement based on the age of the unit.

Retrofit Type

A retrofit type is a distinct type of improvement that is made that influences the use of measures by a unit.

Retrofit Rate

The annual rate at which a retrofit is applied to units. This is specific to each unit type.

Retrofit Properties

Retrofit properties indicate how a retrofit influences the use of a measure for a unit type. For example the retrofit properties specify how a water efficiency retrofit would effect a single family dwelling, and there could be distinctly different properties for how the same retrofit changes water use in a mult-family dwelling unit.

Operational Example:

Assuming that you have python (any recent version of Python2.X) installed, have access to a PostgreSQL instance with an "urbanfootprint" database created, and the sample input parameters in a folder called "InputData" in the same folder with BuildingMix.py, the following is an example of its use in a basic scenario. Comments in the code on the what the code is doing are in grey preceeded by a # sign. Additional comments added for this document are in red.

```
if __name__ == "__main__":
Starting a timer on this process so that we can track how long it takes. Configuring the
connection to the PostgreSQL database, and identifying which scenario we wish to run.
    time.clock()
    database = 'urbanfootprint'
    connstr = "dbname='urbanfootprint' user='postgres' host='localhost' password=''"
    schema = 'hmix'
    sid = 1

Simple cleanup of any prior runs. This type of thing will only be run in rare circumstances. It
is included here for testing purposes.
    #Clean up for testing
    conn = psycopg2.connect(connstr)
    cur = conn.cursor()
    cur.execute("DROP SCHEMA {ischema} CASCADE;".format(ischema = schema))
    cur.execute("CREATE SCHEMA {ischema};".format(ischema = schema))
    conn.commit()
    cur = None
    conn = None

Create the tables through instantiating an object of type MakeTables and instructing it to make
the tables.
    # make Tables
    print str(datetime.datetime.now()),"Starting make tables"
    mt = MakeTables(connstr, schema)
    mt.MakeTables()
    print str(datetime.datetime.now()),"Done"

Load initial data into the tables from CSV files. An object of type LoadTables is created and
handed information about the scenarios to be created and the data to load into them.
    # Inital Loading of Tables
    print str(datetime.datetime.now()),"Starting Load Tables"
    lt = LoadTables(connstr, schema)
    #list of input files and corresponding database table name.
    lt.LoadScenarios(r"InputData/scenario.csv")
    lt.addData([[r"InputData/geo.csv", "hmix_geo"],
                [r"InputData/hu_tots.csv", "hmix_hu_tots"],
                [r"InputData/base_hu_retrofit_rate.csv", "hmix_base_hu_retrofit_rate"],
                [r"InputData/hu_retro.csv","hmix_hu_retro"],
                [r"InputData/hu_class.csv", "hmix_hu_class"],
                [r"InputData/new_hu_retrofit_rate.csv", "hmix_new_hu_retrofit_rate"],
                [r"InputData/redev.csv", "hmix_redev"],
                [r"InputData/new_hu_replace_rate.csv", "hmix_new_hu_replace_rate"],
                [r"InputData/base_hu_replace_rate.csv", "hmix_base_hu_replace_rate"],
                [r"InputData/rlag.csv", "hmix_rlag"],
                [r"InputData/floor.csv", "hmix_floor"],
                [r"InputData/base_usage.csv", "hmix_base_usage"],
                [r"InputData/retro_props.csv", "hmix_retro_props"],
                [r"InputData/newanneffimp.csv", "hmix_newanneffimp"],
                [r"InputData/base_usage.csv", "hmix_base_usage"],
```

```
                [r"InputData/new_usage.csv", "hmix_new_usage"],
                [r"InputData/baseanneffimp.csv", "hmix_baseanneffimp"],
                [r"InputData/newbaselineanneffimp.csv", "hmix_newbaselineanneffimp"],
                [r"InputData/measures.csv", "hmix_measures"]]
               ,1,1)
    print str(datetime.datetime.now()),"Done"
```

Create an object of type ExpandTables and instruct it to expand the appropriate tables.

```
    # Expand Tables
    print str(datetime.datetime.now()),"Starting Expansion"
    et = ExpandTables(connstr, schema)
    et.ExpDef(sid, expmode)
    print str(datetime.datetime.now()),"...Complete"
```

Create an object of type BuildingMix and inform it of which database schema contains the input data, and which scenario should be evaluated.

```
    bmix = BuildingMix(sid, schema)  #this assigns bmix as "self"
```

Load the needed information for the scenario into memory for use.

```
    bmix.LoadFromDB(connstr)
```

An alternate method for specifying all inputs to the model. This can allow building mix to be run independently of the database.

```
#    bmix.LoadSampleData(geoids, syear, eyear, ity, binv, brr, nrr, rlag, mbr, rettypes, bretr, nretr, targets)
```

Run the main building inventory process to generate the number of units by year of manufacture and type in each year. And, write the results to database.

```
    bmix.MainProc()
    bmix.WriteToDB()
```

The remaining calculations are all run in memory because it takes less time to evaluate the results than to write and then read them from the database.

Run the retrofit calculations to generate the number of units by type and year with each type of retrofit in each year.

```
    bmix.DoRetrofits()
```

Run the calculation to generate the total amount of each measure consumed by units and type including the discounts from each retrofit.

```
    bmix.CalcMeasures(bmix.measures, bmix.base_usage, bmix.baseanneffimp, bmix.new_usage, bmix.newanneffimp, bmix.newbaselineanneffimp, bmix.retroprops)

    # Base inventory
```

Print the number of units remaining by type from the base inventory in 2020.

```
    print "Remaining Base Inventory:",bmix.bi[1][2020]
```

Print the number of remaining base units by type in 2020 with retrofit type 1

```
    # Number of Units with Retrofits
    print "Remaining base units in 2020 with Retrofits", bmix.RetroUnits[2020][1]['base']
```

Print the number of new units built in 2015 by type in 2020 with retrofit type 1

```
    print "New units made in 2015, with retrofits in 2020", bmix.RetroUnits[2020][1]['new'][2015]
```

Print the total used of each measure as a baseline usage, the discount, and the net useage for all units that exist in each year. This is summed to create total energy used. Also reported are the totals by unit type.

```
    ms = bmix.SumMeasures(2010,2020)
    for meas in measures:
        print meas,'baseline', ms[1][meas]['baseline']
        print meas,'discounts', ms[1][meas]['discounts']
        print meas,'net', ms[1][meas]['net']
        for it in ity:
            print meas,"Unit type", it,'baseline', ms[1][meas][it]['baseline']
            print meas,"Unit type", it,'discounts', ms[1][meas][it]['discounts']
            print meas,"Unit type", it,'net', ms[1][meas][it]['net']
    print time.clock()
```

Fleet Mix:

The Basics:

A flexible framework for formulating passenger vehicle fleet mix scenarios has been created to enhance the ability of UrbanFootprint to estimate transportation-related GHG emissions into the future. Assumptions about new vehicle performance, market share of different vehicle types, and vehicle retirement rates are loaded into this model to determine the aggregate fuel and energy efficiency of the on-road fleet in any year. When combined with an estimate of vehicle miles traveled (VMT), and applying the assumption that each vehicle is driven equally, we may calculate fuel and energy demand, and resulting GHG emissions.

From a technical standpoint, the newly developed fleet mix model, coded in Python, bears many structural similarities to the building inventory model. An initial base fleet is defined as the total number of vehicles on the road proportioned by type. This initial fleet is subject to differential retirement rates, by vehicle type, of these vehicles from active use. Vehicles that retire from the base fleet are either not replaced, in the case of net decreases in vehicles, or become part of a pool with net fleet growth, and subsequent retirement from the new vehicle fleet, that is distributed into new vehicles based on an assumed mix of vehicles sold in each year.

It is worth noting that that the Fleet Mix model was coded before the Building Mix model. Some improvements to the underlying code that were included in the Building Mix model have not yet been included in the Fleet Mix model, though those will work their way into place in the near future.

Fleet size is an exogenous input, and may be derived from other outputs such as the vehicle ownership estimate in the MXD based travel engine in UrbanFootprint. The distribution of vehicles by type in annual vehicle sales may be drawn from several sources with past examples drawn from the California Air Resources Board, Office of Planning and Research, and the Energy Information Administration.

Technical Description:

The fleet mix model is coded in Python, written to be flexible and have run times measured in seconds that would allow its easy use within a live public outreach session and will be linked to the user interface of UrbanFootprint. With simple modifications, the fleet mix model cold be portable to other applications. The model includes four basic steps:

1. Load data and policy assumptions from the UrbanFootprint Core
2. Calculate fleet mix for each year including calculations of the base and new fleets.
3. Application of vehicle efficiency and emissions rates to generate summaries of criteria measurements, currently VMT, natural gas, and water, though that list is expandable.
4. Writing results to database.

In the data loading step, the net change by vehicle type in a geographic area, referred to as a "Geoid," is calculated and handed to the vehicle mix model. A Geoid may be defined flexibly, but is intended to provide localization of the land use change at a scale that can represent significant differences in policy or social environment. The net change in vehicles is preprocessed to provide the incremental change in number of vehicles each year.

The number of vehicles by type in the initial year is referred to as the base fleet. Vehicles may only be retired out of the basefleet, no new vehicles may be created into it. All new vehicles, either replacements for retired members of the base fleet or coming from net fleet growth, become members of the "new fleet." Vehicles in the new fleet may also be retired from use. Their replacements become new members of the new fleet.

The net change in vehicles creates a running account of the number of new vehicles that need to be added to the new fleet. Retirements from both the base and new fleet are added to this total number of new vehicles created in each year. This total is then allocated into vehicle types based on a projected (as an input to the fleet mix model) proportion of vehicle sales for each vehicle type and added to the new fleet as a vehicle of that type entering use in the specified year. In this way, we can track the number of vehicles in the new fleet in use in each year by the year of vehicle manufacture.

Base fleet retirement occurs as by fixed rates. Members of the base fleet are retired based on a vehicle type specific rate of retirement. i.e. internal combustion engine vehicles may retire out of the base fleet more quickly than diesel vehicles.

New fleet retirement occurs at a vehicle type and age specific rate. The annual rate of retirement for a vehicle type and age is governed by equation 3.

$$r_e = r_a * f_t \qquad \text{Equation 3}$$

Where

r_a is the base rate of retirement for a vehicle of a specified age(a)

f_t is a factor that adjusts the base rate of retirement based on the vehicle type(t)

r_e is the effective retirement rate for a vehicle of type t and age a

This process results in us knowing for each year, how many vehicles of each type remain from the base fleet, and for the new fleet we know, for each year, how many vehicles remain in use manufactured in each preceding year.

Impact assessment is conducted through the definition of queries stored as views in the database that are updated automatically as the underlying fleet mixes change.

Depending on system load, and number of years being analyzed, the fleet calculations can take two seconds per Geoid. Because each Geoid is effectively independent in the calculation this process is eligible for parallelization though this will require additional coding to fully implement.

Programming Notes:

The Fleet Mix tool set is constructed as a set of Python classes that provide the needed functionality to run the fleet mix and impact analysis. Each class fills a specific role and is a largely self-contained unit for accomplishing its designed tasks.

These classes are:

These classes are:

MakeTables:

MakeTables creates the needed tables within the underlying PostgreSQL database to store the inputs and outputs of the fleet mix model. This class should only need to be used once as the tables are not created or destroyed (dropped) by the subsequent model components. In the future this class will be replaced for UrbanFootprint's use by a Django models.py

LoadTables:

LoadTables imports a set of comma separated value (csv) tables into the database to populate initial parameters for fleet mix, growth, replacement, efficiency, and impacts.

Interpolate:

The interpolate class provides a calculator that takes two values for two known years (eg. 2010 and 2020) and provides values for each intervening year based on an assumed linear change between the two known years.

ExpandTables:

ExpandTables generates expansions of input data to represent the extrapolation of trends represented in the input years into annual factors where needed. This automates the interpolate option across all needed variables.

FleetMix:

FleetMix is the central component of the model. It loads all needed inputs from either the database tables, or when run in a testing mode from direct inputs, and executes the fleet mix methods on all vehicle types, over all years between the specified start and end years. Results are recorded into the database.

Some Terminology:

Scenarios (sid)

The FleetMix model is setup to allow flexibility in analyzing different policy scenarios or geographic areas. Each configuration of the fleet mix module is considered to be a scenario and is assigned a Scenario ID (sid) and a user defined scenario name. A scenario is a complete set of configuration information that includes all inputs, settings, and outputs.

Geoid

Scenarios also include geographic sub areas (or geoids). These exist to provide support for tracking differences in selected subareas for analysis. If no subareas are highlighted for analysis then the entire region may be considered a single geoid.

Scenarios may be copied and updated with new data or policy settings to create new scenarios.

Vehicle Type

A vehicle type is a generic definition of a type of vehicle. This includes the type of fuel used by the vehicle, and is the key to which all efficiency information for the vehicle is joined.

Base Year

The starting year of the fleet model.

Horizon Year

The final year of the fleet model

Base Fleet

The number of vehicles of each vehicle type that are on the road in the base year. Remaining members of the base fleet are tracked annually throughout the model run until the horizon year.

Base Fleet Turnover/Replacement

A vehicle type specific annual rate of retirement for members of the base fleet

New Fleet

A holding structure that maintains records on the number of vehicles added to the on-road fleet through replacement out of the base fleet, replacements from the new fleet, and net growth in total fleet size. This includes tracking the number of vehicles on the road in each year by the year of manufacture.

New Fleet Turnover/Replacement

The basic annual rate of replacement for a vehicle by age of vehicle. This is not vehicle type specific, that is dependent on the vehicle type factor described below.

New Fleet Turnover/Replacement Vehicle Type Factor

An adjustment rate applied to the New Fleet Turnover rate that to create a vehicle type specific replacement rate by vehicle age.

Vehicle Miles Traveled (VMT)

An externally sourced, likely from the MXD module, source of the total number of vehicles miles traveled. This is used in conjunction with the on-road fleet to determine how many miles are traveled by the vehicles of each vehicle type (by age of vehicle).

Vehicle Efficiency

The fuel efficiency of each vehicle type, by year of manufacture, and fuel type. This is used to determine the average on road fleet efficiency and the quantity of fuel used in each year.

Impact Conversion Factors

These are factors used to convert the number of miles traveled by each vehicle type by age of vehicle, and fuel efficiency into costs of vehicle operation, pollutant emissions, or other impact measures. This system is flexible, and extensible.

Operational Example:

Assuming that you have python (any recent version of Python2.X) installed, have access to a PostgreSQL instance with an "urbanfootprint" database created, and the sample input parameters in a folder called "InputData" in the same folder with BuildingMix.py, the following is an example of its use in a basic scenario. Comments in the code on the what the code is doing are in grey preceeded by a # sign. Additional comments added for this document are in red.

```
if __name__ == "__main__":
Initialize clock for monitoring system performance
    time.clock()

Open Database Connection
    database = 'urbanfootprint'
    connstr = "dbname='urbanfootprint' user='postgres' host='localhost' password=''"
    schema = 'fmix'
    sid = 1
    expmode = 1 # vehicle based = 0, per cap based = 1

Empty the database for testing purposes. This code is used only for testing or initialization of the
database
    # Clean up for testing
    conn = psycopg2.connect(connstr)
    cur = conn.cursor()
    cur.execute("DROP SCHEMA IF EXISTS {ischema} CASCADE;".format(ischema = schema))
    cur.execute("CREATE SCHEMA {ischema};".format(ischema = schema))
    conn.commit()
```

```
    cur = None
    conn = None
```

Create the needed tables to store inputs and outputs

```
    # make Tables
    print str(datetime.datetime.now()),"Starting make tables"
    mt = MakeTables(connstr, schema)
    mt.MakeTables()
    print str(datetime.datetime.now()),"Done"
```

Load base data into the tables.

```
    # Inital Loading of Tables
    print str(datetime.datetime.now()),"Starting Load Tables"
    lt = LoadTables(connstr, schema)
    #list of input files and corresponding database table name.
    lt.LoadScenarios(r"InputData/scenario.csv")
    lt.LoadFuelType(r"InputData/fuel_type.csv")
    lt.LoadVehicleClasses(r"InputData/vehicle_class.csv")
    lt.addData([[r"InputData/impact_assumptions.csv", "fmix_impact_assumptions"],
                [r"InputData/new_fleet_sales.csv", "fmix_new_fleet_sales"],
                [r"InputData/new_fleet_eff.csv","fmix_new_fleet_eff"],
                [r"InputData/new_fleet_turnover.csv", "fmix_new_fleet_turnover"],
                [r"InputData/pop.csv", "fmix_pop"],
                [r"InputData/vmt.csv", "fmix_vmt"],
                [r"InputData/new_fleet_turnover_vcdf.csv", "fmix_new_fleet_turnover_vcdf"],
                [r"InputData/base_fleet_efficiency.csv", "fmix_base_fleet_efficiency"],
                [r"InputData/base_fleet_mix.csv", "fmix_base_fleet_mix"],
                [r"InputData/base_fleet_turnover.csv", "fmix_base_fleet_turnover"]],1)
    print str(datetime.datetime.now()),"Done"
```

Execute the expand operation to calculate annual inputs from inputs provided as point in time data

```
    # Expand Tables
    print str(datetime.datetime.now()),"Starting Expansion"
    et = ExpandTables(connstr, schema)
    et.ExpDef(sid, expmode)
    print str(datetime.datetime.now()),"...Complete"
```

Run the Fleet mix model (specifying input parameters)

```
    # Run Fleet Mix
    print str(datetime.datetime.now()),"Starting Fleet Mix Script..."
    baseyear = 2005
    endyear = 2050
    sid = 1
    startfleet = 737 (a vehicle population correction factor applied to match the reference model)
```

Create an object of type FleetMix and initialize it with input parameters)

```
    fmbf = FleetMix(connstr, schema, sid, baseyear, endyear, startfleet)
```

Run the sequencer that controls program flow and calculates the on-road vehicle fleet for each year between the base year and end/horizon year.

```
    print str(datetime.datetime.now()),"Starting Sequencer"
    fmbf.Sequencer()
```

Write fleet data into the database

```
    print str(datetime.datetime.now()),"Starting Write Tables"
    fmbf.WriteTables()
```

Create or refresh the views that contain easier to access model outputs for on-road fleet and impacts

```
    print str(datetime.datetime.now()),"Starting Views"
    fmbf.AnnualNumericalTotals()
    fmbf.MakePMView()
```

Close database connection and cleanup.

```
    fmbf.CloseConn()

    print str(datetime.datetime.now()),"Fleet Mix Script Complete!", str(time.clock())
```

Appendix 3: UrbanFootprint: Transportation Model Enhancement Framework

Calthorpe Associates | Fehr & Peers (under subcontract to ULTRANS, UC Davis)

This document describes a framework of advancements that will strengthen the capacity of the UrbanFootprint model to evaluate the greenhouse gas (GHG) reduction potential of regional and local transportation strategies. The prioritization of these improvements has been guided by the UrbanFootprint Technical Advisory Committee (TAC), convened to advise on improving the model for use in GHG and other analyses. Based on discussions during the November 28, 2012 and March 13, 2013 TAC meetings and subsequent email communications, planned enhancements and related tasks were identified and classified as either Tier 1 (near-term, within project scope) or Tier 2 (longer-term) priorities.

Both the Tier 1 and Tier 2 improvements are described here. The Tier 1 priorities extend RTP/SCS modeling capacities in the areas of regional transportation demand management (TDM) policies and congestion effects. The Tier 2 priorities are planned as next steps towards improving the accuracy and policy sensitivity of the model; they include: additional TDM strategies that may be deployed at the regional or specific plan levels, commercial truck travel modeling, integration with activity-based models, internalized network analysis, and transit level-of-service analysis.

In addition to the technical advances described below, Tier 1 documentation will include:

- The distinction between scenario planning and project-specific analysis. UF serves the first purpose, but is not a substitute for other tools that would perform the final analysis of: a) individual development projects (local impact analysis tools such as Plan+), b) changes in transportation infrastructure (regional travel models), congestion and induced travel (regional travel models), truck flows (freight models).

- Additional sensitivity testing of UF responses to changes in various input assumptions individually and in combination.

The current and planned model advancements are outlined in the following sections, along with a description of the technical approach for each. Further discussion will lead to the incorporation of these and other potential advancements into a comprehensive development plan, including identification of funding pathways.

Transportation Demand Management (TDM)

The current Tier 1 project work plan includes the technical specification of methods to model the impacts of regional-scale TDM measures in UrbanFootprint. These measures, selected for their relevance to regional planning and policy setting, include:

- Pricing, applied as automobile operating cost increases due to fuel and VMT charges. (Identified as one of the most important TDM strategies by the TAC).
- Parking pricing (and the ability to apply this within specific areas)
- Transit service improvements, including frequency and speed
- Employer trip reduction programs, including transit fare subsidies, alternative work schedules, and telecommute programs

Technical Approach

The individual effects of these measures will be combined into overall VMT reductions. Quantifying these relationships in UrbanFootprint is based on relationships reported in *Guidelines for Quantifying the GHG Effects of Transportation Mitigation*, published by the California Air Pollution Control Officers Association (CAPCOA). CAPCOA TDM effectiveness estimates take into account the effects of location and setting on potential effectiveness of individual strategies. To capture this functionality, UrbanFootprint correlates its place type categories with the locational categories used in the CAPCOA analysis.

The ability to evaluate such strategies on more localized levels of application, namely the Specific Plan level, is likely to be undertaken as part of Tier 2 efforts. Additional TDM strategies will be evaluated using relationships and elasticities derived from national and California research. The CAPCOA document will be a primary source, supplemented by other sources, including: research briefs by professors Handy and Boarnet for CARB in conjunction with SB 375; the books *Growing Cooler* and *Moving Cooler*; the Transportation Research Board report *Driving and the Built Environment*; and effectiveness estimates produced by the Center for Clean Air Policy.

These studies indicate that there is a range of effectiveness potential for each TDM strategy and combinations of strategies. The effectiveness level varies based on the geographic scale of application, the context within which a measure is applied, how intense the application, the presence or absence of supporting strategies, and how the measures themselves impact travelers' decisions when they are translated into travel cost, travel time, and the relative differentials in cost and time among competing travel modes.

Equipping UrbanFootprint with the ability to estimate the effectiveness of the measures will depend on the ability to import network summary information from the MPO travel models that is sufficient to assess the traveler time and cost differentials the measures produce in different situations. The process will involve lookup tables for relevant place type-oriented equations or elasticities from CAPCOA and the other research findings that will be measured in terms of changes in travel times and costs and accounting for any socio-demographic characteristics associated with the place type.

Congestion Effects

UrbanFootprint now has the capability to perform an approximate aggregate estimate of regional congestion. However, the model does not contain the transportation network analysis capabilities that would be required to perform location-specific congestion analysis.

Technical Approach

The UrbanFootprint procedure draws systemwide information on overall highway network capacity from the MPO travel models' transportation network summaries. The systemwide totals of lane miles by facility class are used to ascertain each region's transportation network supply, expressed in terms of the number of existing and future lane miles of freeway, arterials, and local streets.

This information is compared with UrbanFootprint estimates of regional VMT to derive average regional travel speeds based on VMT/lane mile ratios. The ratios are translated into estimates of VMT by travel speed range, based on traffic data collected in over 100 regions across the US over the past 20 years by the Texas Transportation Institute (TTI). The conversion is based on relationships between the TTI regional congestion indices and regional VMT per lane mile, developed by the Oregon Department of Transportation for its GreenSTEP model. An analytic spreadsheet has been provided to allow recursive application of the method to produce convergence on a stable estimate of average regional congestion for freeways and for arterial streets.

Commercial Truck Travel Modeling

UrbanFootprint could be further enhanced to explicitly model growth in truck traffic. The present and Tier 1 versions of the model use truck traffic forecasts produced by official state and regional sources outside of UrbanFootprint. As part of Tier 2 improvements, UrbanFootprint could be equipped with the means to estimate commercial light-duty truck travel at the regional level. As heavy-duty and medium-duty (HD and MD) trucks travel is not covered by SB 375, modeling these modes would be deferred to a post-Tier 2 phase of UrbanFootprint upgrades.

Technical Approach

Commercial LD vehicle traffic generated by offices, shopping centers and household are included the ITE and MXD trip generation rates used in UrbanFootprint. Tier 2 model improvements will require the latest information of commercial trip generation by ITE land use category, translated by Fehr & Peers into rates for UrbanFootprint place types.

Integration with Activity-Based Models

UrbanFootprint could potentially include an option to use an MXD-derived (or other equivalent) travel methodology that is based on an activity-based, rather than a 4-step, modeling framework. This will allow for accounting of commercial vehicle characteristics and trips at sub-regional scales, and improve the ‘handshake’ to models such as the Sacramento Area Council of Government’s (SACOG) SACSIM and other MPO activity models. Adding this capability to UrbanFootprint will be considered for inclusion in Tier 2 for MPOs who do not add truck estimation capabilities themselves through individual contracts with the Calthorpe team for UrbanFootprint model implementation.

Technical Approach

California’s largest MPOs have developed Activity Based Models (ABMs) to replace their more conventional 4-step trip-based models for RTP & SCS development and other regional analyses. Presently, UrbanFootprint interacts with the MPO models in a manner that allows it to draw trip tables and skim matrices used by both ABM and trip-based models. However, a desired improvement would be to allow UrbanFootprint to more seamlessly interact with the MPOs’ primary models on the basis of travel tours, rather than to simply deal with individual trips. This will involve several changes to data conversion protocols for UrbanFootprint.

Proof-of-concept and initial examples of ABM integration are likely to be implemented as part of separate work the Calthorpe team is currently undertaking with SACOG and SANDAG. The approach may entail translating the UrbanFootprint MXD-derived travel methodology to a similar method developed by Caltrans, SACOG, UC Davis and Fehr & Peers in the form of “Sketch 7” analysis modules. One approach may involve breaking trip tours into zonal trip tables and applying UrbanFootprint to the trips extracted from the tours. The Sketch 7 analysis process is being implemented in a fashion that can translate and exchange data with SACOG’s SACSIM and other activity-based models.

Internalized Network Analysis Capabilities

Network analysis incorporates transportation networks and pathways into proximity calculations, allowing for a more sophisticated measurement of proximity as compared to conventional Euclidean methods (as used by UrbanFootprint v1.0). It is likely that a phased approach would be required to implement network analysis capabilities. For instance, an initial focus may be put on auto and pedestrian networks, with transit and bicycle networks added in later phases.

Technical Approach

Network analysis uses transportation networks that represent automobile, transit, pedestrian or bicycle-accessible links, with weights (speeds and costs of travel) applied accordingly to assess spatial relationships between locations. The potential use of a network analysis varies for each mode, as does the complexity of the problem of assembling a validated network for both the base year and for future scenario horizon years. Automobile network analysis would allow more accurate analysis of traffic congestion effects. A pedestrian network analysis, for instance, would be useful for the purposes of generating a network buffer that could be used to analyze urban form attributes of an area around an analysis geography (grid cell or parcel) for attributes, such as average retail FAR, that are known to contribute to levels of active transportation. Such a network analysis would allow UrbanFootprint to become sensitive to barriers (such as lengths of freeway without over- or under-passes to allow pedestrian permeability) that separate neighborhoods from adjacent retail areas.

If undertaken, the process of adding network analysis capabilities would involve creating the ability to add and remove transport links (such as new roads, rail alignments, and stations) through painting (or automated and import processes), network building, and debugging; incorporating computed time and cost parameters; internal multi-segment path tracing and network skimming; internal mode choice functionality; reiterative feedback loops to allow network function to affect trip generation, destination choice, and route choice; and the ability to report key network performance metrics on the fly.

Transit Performance and Level-of-Service (LOS) Analysis

UrbanFootprint could be advanced to include model intelligence with regards to transit level of service and fleet operations as a basis for estimating the emissions impacts of transit vehicle movement based on transit vehicle fleet characteristics. Intelligence to make mode choice and VMT sensitive to transit LOS would be a Tier 2 advancement. Emissions impacts sensitive to transit vehicle speed may be added beyond Tier 2.

Technical Approach

Transit Level-Of-Service measurement is a complex and evolving field that potentially includes many factors[1]; various indices have been developed that seek to measure certain characteristics or others. An approach involving a Local Index of Transit Availability, for instance, may offer an appropriate level of detail for the purposes of integration with other UrbanFootprint analysis engines; on the other hand, a full Transit Level of Service Indicator that looks at demand as well as availability may be preferred to

[1] See http://www.vtpi.org/tdm/tdm129.htm; in particular, Tables 8-10.

ensure that levels of development match transit service levels. Further research will be required to determine which measure(s) of transit LOS would be appropriate to include in UrbanFootprint, and the exact technical advancements required.

Adding the impacts of transit operations emissions to a transit LOS analysis could involve an additional series of steps beyond adding internalized transit network analysis capabilities (as discussed in the preceding section). If adding transit network capabilities proves to be justified, implementing additional model intelligence to address transit performance would enable UrbanFootprint to estimate the emissions impacts of transit vehicle movement based on transit fleet characteristics. One approach to making Urban Footprint mode choice and VMT estimates sensitive to transit service would involve enhancements to add a network-based model capable of modeling link-specific speeds and node-specific delays for different volume loads and by individual vehicle classes.

Interregional Travel and Goods Movement

Caltrans and ARB expressed interest in coordinating the Urban Footprint estimate of interregional travel with estimation performed by Caltrans Statewide Transportation Model. Related objectives would include forecasting interregional goods movement and incorporating the SB 375 method of assigning responsibility for the generation of interregional VMT.

Technical Approach

Adding capabilities related to interregional travel and goods movement would involve adding the ability to interact with existing statewide models (California Statewide Travel Model, California Freight Model, High Speed Rail travel model). Trip tables and skim matrices from these models would be imported to UF and applied in much the same way as UF currently uses imported tables to compute accessibility and VMT. The approach could also give Urban Footprint the ability to estimate the effects of land use policy on high speed rail ridership.

Appendix 4: Water-Energy Briefing for Urban Footprint Model

Ned Spang, Ph.D.
Center for Water-Energy Efficiency

<u>Overview</u>

There are two pathways to saving energy in the water sector. One pathway is to use more energy efficient devices associated with water use (e.g. water heaters, dishwashers, washing machines.) This pathway is captured in Figure 1 as the top horizontal flow of using more energy efficient devices.

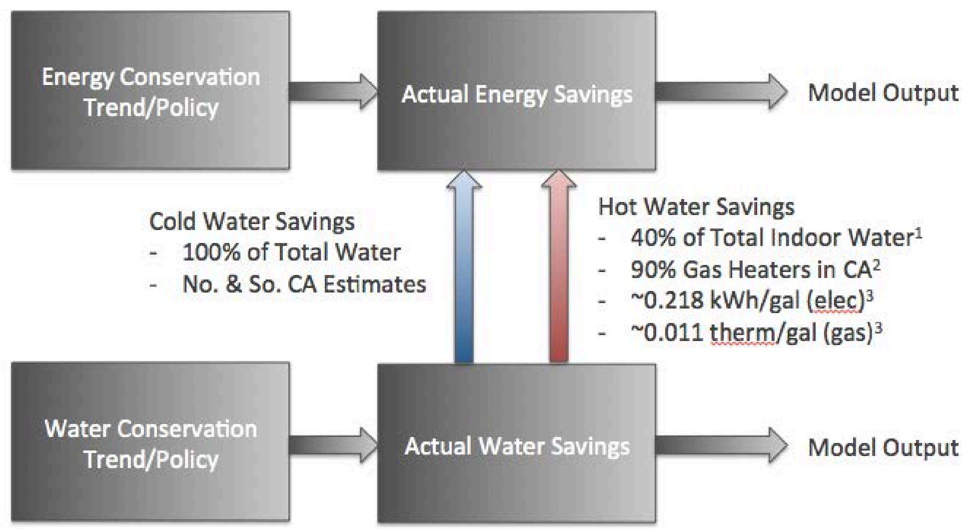

Figure 1. Residential Water-Energy Conservation Interaction

The second pathway is to reduce water use and thereby save the "embedded energy" within the water. This pathway includes both "cold water" energy savings and "hot water" savings (represented by blue and red arrows in Figure 1). The cold-water energy represents all the energy requires to extract, treat, and deliver water, as well as to treat the resulting wastewater (see Table 1). This energy applies to all the water used in the home.

	Indoor Uses		Outdoor Uses	
	Northern California kWh/MG	Southern California kWh/MG	Northern California kWh/MG	Southern California kWh/MG
Water Supply and Conveyance	2,117	9,727	2,117	9,727
Water Treatment	111	111	111	111
Water Distribution	1,272	1,272	1,272	1,272
Wastewater Treatment	1,911	1,911	0	0
Regional Total	**5,411**	**13,022**	**3,500**	**11,111**

Table 1. Northern and Southern California Cold-Water Embedded Energy Estimates[4]

Energy Savings through Water Conservation

The hot-water energy represents the additional energy added by the end-user to heat the water. In residential settings, hot water represents roughly 40% of all indoor water use.[1] Meanwhile, 90% of water heaters in California are powered by natural gas[2] (requiring ~.011 therms/gal)[3] leaving 10% of water heaters powered by electricity (using ~0.218 kWh/gal)[3].

Hence, if one million gallons of indoor residential water were saved in a Northern region of California, then the following embedded energy savings could be claimed:

Cold-Water Savings
1 million gallons (MG) saved * 5,411 kWh/MG = 5,411 kWh saved

Hot Water Savings
Gas Water Heaters = 1 MG * .40 (40% of indoor residential water is hot water) * .90 (90% of CA water heaters are gas-powered) * 11,000 therms/MG = 3,960 therms saved

Electric Water Heaters = 1 MG * .40 (40% of indoor residential water is hot water) * .10 (10% of CA water heaters are electric-powered) * 218,000 kWh/MG = 8,720 kWh saved

Total Energy Savings
Electricity savings= 5,411 kWh + 8,720 kWh = 14,131 kWh
Gas savings= 3,960 therms

Energy Efficiency Value of Water Conservation (using approximate values from PG&E)
Electricity = 14,131 kWh * 0.10 $/kWh = $141.31
Gas Savings = 3,960 therms * 1.00 $/therm = $3,960

Both of these values can then be easily converted into GHG emissions savings as well as other economic and environmental factors contained in the UrbanFootprint model.

Model Challenges

Unfortunately, calculating energy use for heating water is currently limited to the residential sector in the UrbanFootprint model. The data is not readily available to effectively represent hot water use for the commercial, institutional, and industrial (CII) sectors.[5] However, with Urban Footprint team gaining permission from the California Energy Commissions (CEC) to access to the 2009 Residential Appliance Saturation Survey (RASS) dataset and the 2003 Commercial End-Use Survey (CEUS) dataset, the both residential and CII hot water energy use estimates can be further developed and refined.

In addition, there is another feedback loop in the model that is not addressed in this initial approach. If the model is interpreting particular trends in energy efficiency (e.g. a ten percent reduction in residential energy use across the board), then the water heater energy use per unit water coefficient should be adjusted accordingly. In other words, the energy efficiency assumptions influence the parameters for calculating energy savings through water conservation. This relationship is highlighted via the large blue arrow in Figure 2. While likely not of immediate concern for the current iteration of the UrbanFootprint model, this energy efficiency feedback loop is something to keep in mind for the future design of the model.

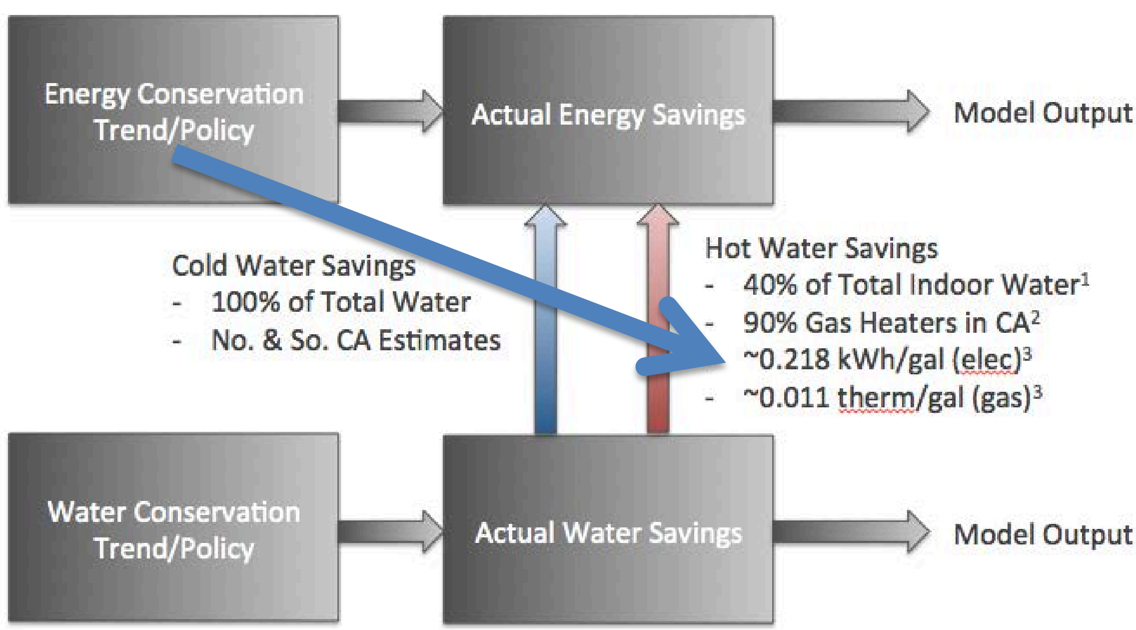

Figure 2. Second Tier Energy Efficiency Interaction with Water Heater Energy Use Estimate

Water for Energy

The Urban Footprint model is also well-suited to estimate the future water requirements for energy production in the planning region. Given an increase in electricity consumption and a subsequent expansion of electricity generation capacity, more water will be required for thermoelectric cooling and other energy-related water uses. Estimates of these energy related water requirements exist and are constantly being updated and refined to incorporate more context-specific parameters, such as ambient air temperature, humidity, and cooling water temperatures.[6] Future iterations of the UrbanFootprint model should apply the best available estimates for water use by electricity generation technology to best estimate the water implications of various energy pathways as driven by both demand and supply.

Next Steps

- Increase granularity of cold water energy intensity estimates by hydraulic region and by individual water agency, where possible.
- Using 2009 RASS data, refine estimates of residential hot water end use and energy intensity by region, building type, and other relevant parameters.
- Using 2003 CEUS data develop CII hot water end use and energy intensity estimates by region, CII category, and other relevant parameters.
- Resolve model feedback structure between increases in energy efficient appliances (including hot water heaters) and projected energy savings from water conservation (as described in Figure 2).
- Increase granularity of water consumption estimates for electricity generation technologies deployed across the state.

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Appendix 5: Energy Consumption Modeling

Building operations account for an important portion of total energy consumption. As part of the process of update of the UrbanFootprint model, we focused on the refinement of the estimation of the energy consumption baselines for this model, in order to improve the ability to predict the quantity of energy consumed in the building stock depending on the characteristics of the building units, their size and geographical location. The correct estimation of the energy consumed in both residential and non-residential buildings, and of their relationships with the characteristics of the building units, is an important feature to include in land use modeling studies. For instance, the inclusion of an explicit energy consumption modeling component in a land use modeling framework can allow useful applications for the prediction of short-term and long-term energy consumption patterns depending on the location decisions of firms and households and the type of land use development in an urban area. In a relevant previous experience, Chingcuanco and Miller (2012) integrated a model of energy use for residential space heating demand in the ILUTE model for the City of Toronto, Canada. The resulting residential space heating model component is added to the modeling framework as the first step towards the creation of an integrated energy-land use model that can study energy consumption in the urban area and provide forecasts for future trends of energy consumption depending on the evolution of land use. In a more recent experience, Circella et al. (2013) developed an analysis of energy consumption in the building stock in Los Angeles County using energy consumption data provided by local utility companies, as a step for the update of the PECAS modeling framework with the inclusion of a building operation energy consumption model component for the estimation of energy consumption associated with the built environment.

As part of the process of update of Urban Footprint, and in order to support the improvement of the baseline energy assessment for the existing building stock, we obtained access from the California Energy Commission to the 2009 Residential Appliance Saturation Survey (RASS) dataset. The RASS dataset contains information collected from 24,555 total housing units in the State of California, and include a rich set of variables that can be useful for the analysis of energy consumption in residential units. In the RASS dataset, energy consumption data are reported for both electricity and natural gas over a period of one year, and they include both monthly and annual consumption data for each housing unit. In addition, information about the size of the building unit, the geographical location and the basic household sociodemographics (including level of income) are reported for each record, providing important control variables that can be used in the analysis of energy consumption patterns in residential buildings.

We used the RASS dataset in order to support a refinement of the energy consumption patterns for both electricity and natural gas in the Urban Footprint model. In particular, the RASS data report information about the location of each residential unit in one of the 16 “Title 24” Building Climate Zones in the state of California. The “Title 24” Building Climates Zones (or “California Climate Zone Descriptions for New Buildings”) are defined as unique climatic zones for the purposes of the definition of Energy Efficiency Standards in California. Each Climate zone has a unique climatic condition that dictates the minimum efficiency requirements for the construction of new building or renovation of existing ones. We classified the information available from the RASS datasets based on the climate zone location and the dwelling type for each unit. Due to incomplete information for any of these variables, we needed to filter our several incomplete records, and the sample size was consequently reduced to 21,110 records. Additional data cleaning was carried out in order to remove records with unreliable information and outliers, bringing the sample size to 19,537 records. Residential units were classified based on the building types used in the Urban Footprint model, Single Family Houses, Townhouses and Apartments/Condos. Table 1 shows the distribution of housing units by dwelling type and building climate zone in the available dataset.

Table 1: Distribution of surveyed housing units by dwelling type and building climate zone

		Dwelling Type				*Total*
		Single-Family Detached	*Townhouse/ Duplex/Row House*	*Apartment (2-4 units)*	*Apartment (5 or more units)*	
	1	93	4	6	6	109
	2	433	53	26	58	570
	3	1117	165	210	390	1882
	4	561	93	60	142	856
	5	243	25	16	37	321
	6	1113	284	277	511	2185
	7	1388	211	147	414	2160
Climate	*8*	1232	180	148	257	1817
Zone	*9*	1779	185	128	407	2499
	10	1673	138	96	193	2100
	11	430	14	22	27	493
	12	1073	121	72	119	1385
	13	928	50	107	86	1171
	14	519	27	43	38	627
	15	315	74	107	112	608
	16	607	43	52	52	754
Total		13504	1667	1517	2849	19537

Unfortunately, some combinations of climate zone and building type have only a small number of records in the dataset, as is the case for apartment/condos and townhouses in several climate zones. From one perspective, this is a minor problem given the limited presence of these types of buildings in several climate zones. This poses a problem for researchers trying to estimate a robust model to predict energy consumption in all climate zones and for all categories of building types. The original plan for the update of the energy consumption baseline in Urban

Footprint was in fact to develop energy consumption models for both electricity and natural gas for each climate zone. However, given the limited sample size for many subcategories of residential units by climate zones, and the large variance for electricity and natural gas consumption observed for several segments of the original sample, we considered the adoption of an alternative approach for the estimation of the updated energy consumption baselines.

A relevant amount of energy consumption in residential units is consumed for heating and cooling residential units. A good measure of the energy needs for heating and cooling purposes in residential units is provided by the number of heating degree days (HDD) and cooling degree days (CDD) that are required in each location based on the local climate pattern and average temperatures during the various parts of the year. The RASS data provide information on the number of heating degree days and cooling degree days for sampled residential units. This information is useful in the estimation of models of energy consumption. In addition, energy consumption is expected to be correlated with the size of the building unit (larger residential units, on average, consume larger amounts of both electricity and natural gas). We also expect that an additional amount of energy consumed will be independent of the size of the residential units, as this will be associated with the minimum plugload and quantity of consumed energy that is consumed in any household for basic needs, and that can be considered independent of the size of the unit. In a regression model for the estimation of the energy consumption, this minimum amount of energy consumption for each residential unit is represented by the intercept.

We estimated multiple linear regression models of energy consumption for both electricity and natural gas in residential units using the RASS data. The models were estimated using the annual total consumption of respectively electricity and natural gas for each residential unit as the dependent variables. Several different model specifications were tested in the development of the building. Table 2 reports the results of the estimated linear regression model for electricity consumption (measured in Kwh/year). Explanatory variables included the size of the building unit (in square feet) for respectively single family houses, townhouses and apartments/condos. The intercept (minimum value of energy consumption consumed by each residential unit, independent from the size of the building unit) is also allowed to vary for the different types of buildings, in order to account for the different energy consumption patterns observed in different categories of buildings. The numbers of heating degree days and cooling degree days provide important information on the variation of electricity consumption depending on the climate characteristics of the area where the housing unit is located. These variables allow the estimation of energy consumption in Urban Footprint to be sensitive to the different climate patterns observed in the State of California, and they provide important information about the variation of energy consumption depending on environmental pattern (providing information on the impact, for instance, of an increase of average temperature or possible modifications in the local climate). Also the estimated coefficients for HDD and CDD are allowed to vary by type of housing unit to account for the different impact of climate patterns on various types of buildings.

In the model estimation, original values for HDD and CDD contained in the RASS data were initially used. However, due to the large amount of missing information for these variables, information on the average number of heating degree days and cooling degree days was filled in using data available for each building climate zone in California. The results reported in Table 2 are from the model estimated using these combined data.

Table 2: Estimated coefficients for the electricity consumption model (N=19,537)

	Unstandardized coefficient	*Std. Error*	*p-value*
Constant	1901.097	151.540	<.001
Townhouse (constant modifier)	-1023.904	509.774	.045
Apartment (constant modifier)	-530.163	312.645	.090
SF size (Sq. Ft.)	2.060	.040	<.001
TH size (Sq. Ft.)	1.537	.199	<.001
Apt size (Sq. Ft.)	.898	.111	<.001
Single Family CDD	1.281	.046	<.001
Single Family HDD	.314	.045	<.001
Townhouse CDD	1.123	.142	<.001
Townhouse HDD	.632	.143	<.001
Apartment CDD	.937	.086	<.001
Apartment HDD	.461	.088	<.001

Weighted Least Squares Regression (R-square = .282).
Note: HDD = Heating Degree Days; CDD = Cooling Degree Days; SF = Single family Housing; TH = Townhouse; Apt = Apartment/Condo.

A similar model of energy consumption was estimated to predict the annual consumption of natural gas of each residential unit. The use of these models of energy consumption to estimate the energy consumption baselines in Urban Footprint introduces several advantages if compared with the previous definition of the energy consumption baselines in this model. First, they refine the estimation of energy consumption, for both electricity and natural gas, which is not forecasted for each residential unit *per se*, but is estimated depending on the actual size of the residential unit. This allows a more accurate estimation of energy consumption patterns in the building stock, and it allows to refine estimation of energy consumption for specific categories of buildings, depending on the size (in square feet) of each residential unit. In addition, the estimation of the updated energy consumption patterns is sensitive to the local climate conditions that can be observed in the various climate zones of California. The different estimated coefficients for the numbers of HDD and CDD allow improving the prediction of energy consumption for both natural gas and electricity in the various climate conditions and building types. For example, a higher number of HDD in a climate zone may lead to different patterns of energy consumption respectively in a single family home or in an apartment, depending on what type of energy source is used for heating purposes (some housing units rely on natural gas for heating purposes, while others primarily use electricity also for heating). Finally, the energy consumption baselines are useful to provide an estimate of the distribution of energy consumption in the existing building stock in California, but they are also sensitive to eventual modifications in the climate patterns in the area of study. Therefore, they can be used to predict eventual adjustments in the energy consumption of the existing building stock, for instance, in case of a variation of climate conditions, as it might happen in the case of an increase of the average temperature in some parts of the year.

However, the proposed modifications that have been introduced in the energy consumption component of the Urban Footprint model still require some refinements: for example, the consumption patterns observed in the RASS data show a rather high dispersion. probably as an effect of other unobserved variables that are not explicitly modeled in Urban Footprint. Understanding what the impact of these other variables is on energy consumption may considerably improve the estimation of the energy consumption in model, and further improve the quality of energy baseline estimates and accuracy of predictions of the modeling framework. In addition, the energy consumption models that have been estimated in this stage of the research are useful to predict energy consumption for several categories of buildings in numerous climate zones. However, they seem to produce rather overestimated forecasts for energy consumption for building located in climate zones with rather extreme conditions, also as an effect of the limited sample size useful for the estimation of models in these areas. This is the case for instance of climate zone 15, for which the energy consumption estimates, in particular for electricity, appear to be rather high. This part of the research requires additional investigation, in order to further improve the prediction of energy consumption for all building types and in all areas of California, perhaps also through the integration of additional data on location climate patterns and/or more detailed investigation of energy consumption in specific contexts. Similarly, we are in the process of acquiring the Commercial End Use Survey (CEUS) data from the California Energy Commission, in order to further improve the energy consumption baseline estimations also for non-residential building units.

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