Land Use Scenario DevelopeR (LUSDR)

Introduction

The Land Use Scenario DevelopeR (LUSDR) is being developed to support a long-range urban growth study in Jackson County Oregon. This growth study is called the Medford Regional Problem Solving (RPS) study because it encompasses the Medford metropolitan area. The purpose of the study is to identify urban reserve areas that will meet the needs of a population that is double the current amount. Urban reserves are areas located adjacent to urban growth boundaries (UGB) that will be brought into UGBs as needed to accommodate growth over the long run. The Rogue Valley Council of Governments (RVCOG), Jackson County and affected cities within the county will use information from the RPS study to designate urban reserves in their comprehensive plans.

LUSDR is being used in combination with the metropolitan area transportation model to evaluate the potential transportation consequences of alternative land use patterns and transportation system additions. The objectives of the modeling are:

1. To develop a moderately large set of plausible future land use patterns consistent with the RPS goals.
2. To test the effects of this set of future land use patterns on the transportation system.
3. To identify the features of land use patterns that most affect transportation performance.
4. To assist in identifying additions to the transportation network needed to serve future development of the urban reserves.

Figure 1 shows the location of the model study area and the model zone structure for the area. Figure 2 shows urban growth boundaries and the RPS growth areas being considered in the study.

Although the RPS study is the impetus and test bed for developing LUSDR, it is in no means intended as the sole application. LUSDR is being developed to serve as a general tool for strategic urban land use and transportation planning and for developing reference land use scenarios for transportation planning. It was developed to address several gaps in land use modeling coverage. Although Oregon's statewide model addresses all areas of the state, its geographic resolution is too coarse to provide land use modeling within most urban areas. The prevalent practice for urban areas is to develop consensus assumptions about the distribution of future land uses. Transportation model forecasts are only as good as these consensus land use forecasts. Moreover, since the consensus land use forecasts are static, the effects of alternative transportation policies can only be evaluated with great difficulty. The Portland metropolitan area has Metroscope for land use modeling, but Metroscope combines higher level market models with lower level GIS models that make it specific to Metro's data architecture. LUSDR provides a land use modeling framework that can be applied in many urban areas using the geographic structure and data of urban transport models along with commonly available tax assessment and buildable lands data.

Figure 1
Medford Metropolitan Modeling Area

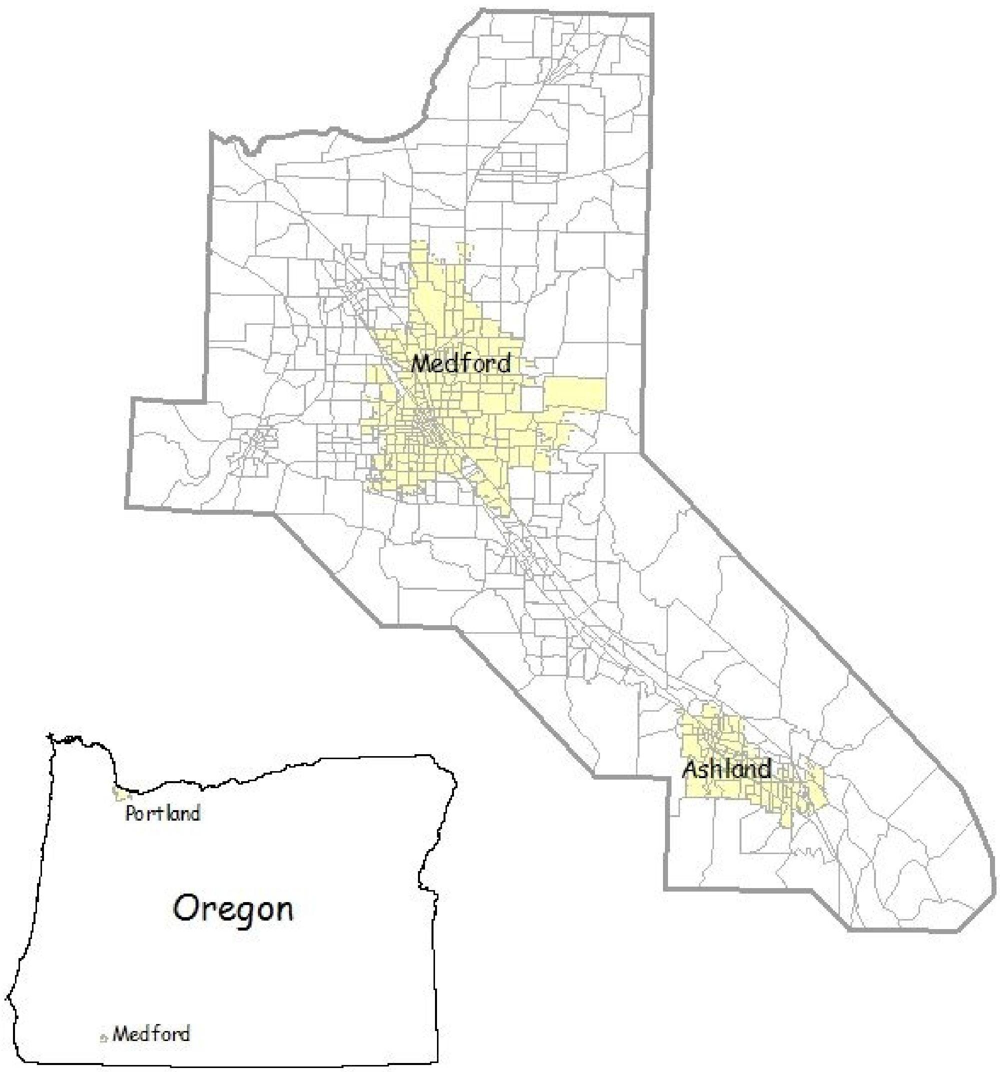
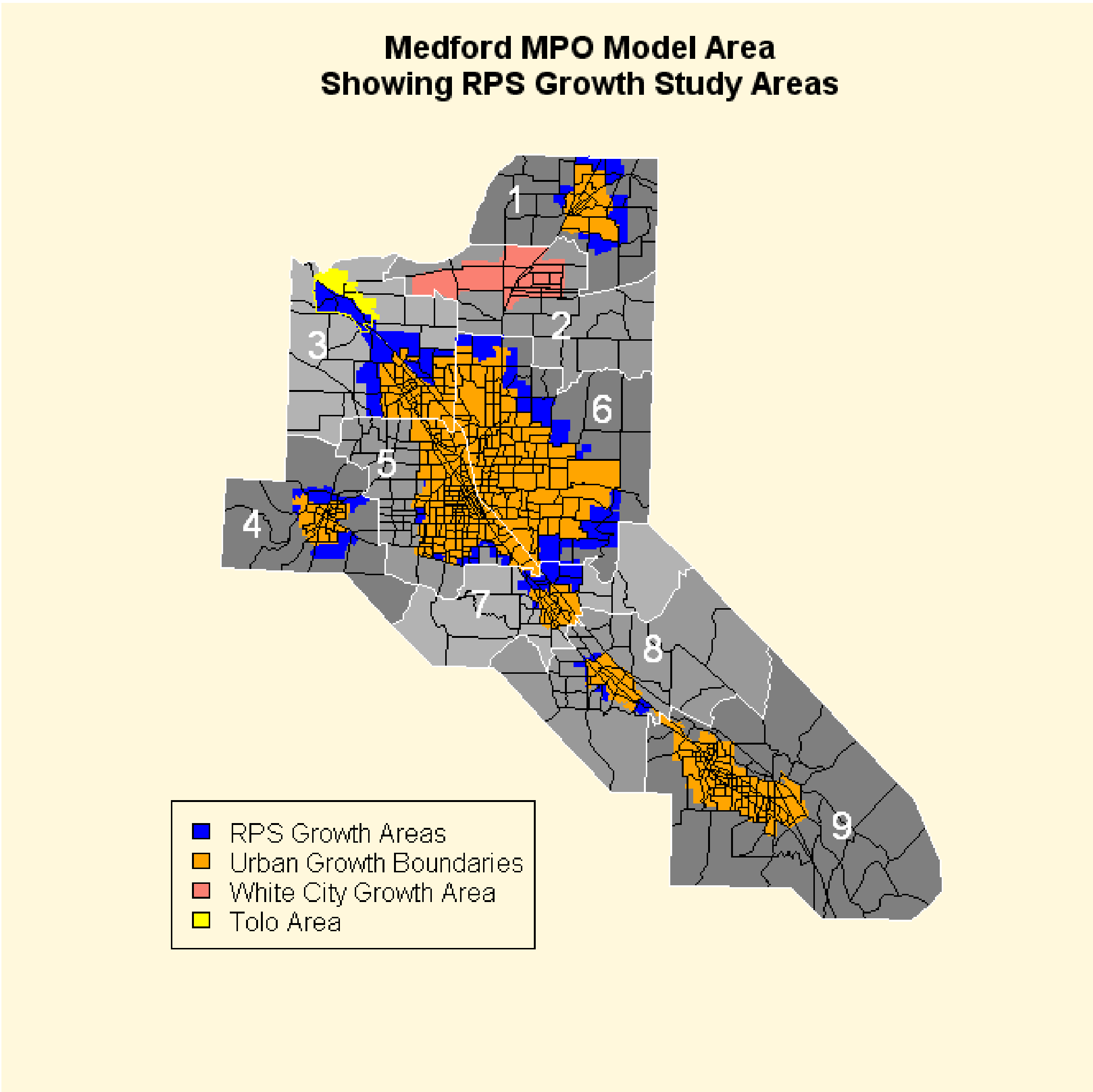


Figure 2
RPS Study Development Areas



LUSDR also fills a strategic planning gap left by most land use models. It is most common for land use models to be equilibrium models. For any combination of transportation and land use policy inputs, they produce one equilibrium solution. In reality, however, land development is affected by many unmodeled factors. For example, a shopping center may be developed on one of several suitable sites (and perhaps not the most desirable site) because of the individual personalities, capabilities and motivations of developers and property owners, and/or because of previous land development actions. Where the shopping center locates can significantly affect the location of other land uses and impacts to the transportation system. Thus an equilibrium forecast may miss important strategic considerations for planners and decision-makers. The LUSDR model fills this gap by producing many scenarios which vary from one-another in many ways but are all consistent with basic location behavior patterns. This enables planning to be done in a more strategic fashion. By comparing the scenarios and their effects, planners can identify the land use arrangements that do a better or worse job of meeting public objectives and to develop transportation and land use policies to achieve a more desired outcome.

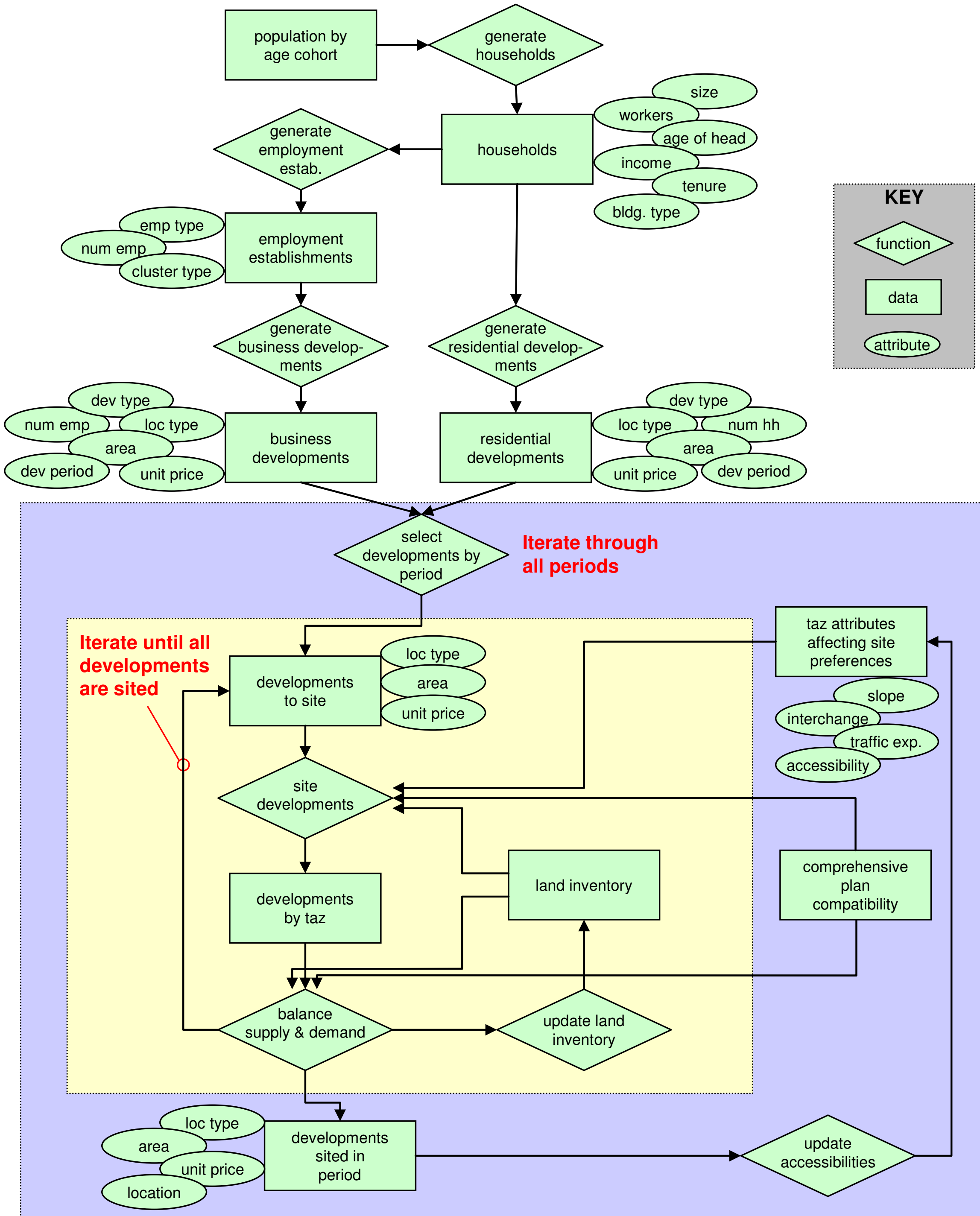
Overview of the Land Use Scenario DevelopeR

LUSDR is a stochastic microsimulation of land development implemented in the R programming language (hence the R in LUSDR). Households, employment establishments and developments are simulated as individual units. Almost all the modeling processes are Monte Carlo processes where outcomes are derived by sampling from probability distributions. The probability distributions come from:

1. Joint probabilities derived from cross tabulations of survey data
2. Terminal node probabilities from decision trees
3. Probabilities derived from smoothing of size distributions
4. Logit model probabilities
5. Expert judgement of land use compatibilities used as probabilities

LUSDR simulates end states rather than transitions. The best approach would have been to model transitions over time: changes in household composition, in-migration and out-migration, changes in business composition, aging of structures, remodeling, demolition and new building. Such an approach, however, would have required considerably more time, resources and data. LUSDR takes a compromise approach which allows “path-dependent” patterns of development to emerge while retaining the simpler and less data intensive end-state approach. The compositions of households, businesses and developments are all simulated for the forecast year, and then assigned randomly to intervening time periods. The location of developments are then simulated by period and accessibilities are updated to inform the location simulation for the next period. Figure 3 is an overall illustration of LUSDR processes.

Figure 3
Overview of LUSDR Processes



LUSDR also has a simplified approach to the land supply side. The best approach would have been to use land parcels as the basis of modelling land supply. This, however, poses many conceptual, modeling and data challenges; for example:

1. People buy and sell parcels;
2. Parcels get split;
3. Parcels are aggregated into ownerships;
4. Developments span parcels in different ownerships (through lease arrangements)

The geographic level for allocating land supply in LUSDR is the transportation analysis zone for the corresponding transportation model. This has the advantage of direct correspondence with the transportation model and having a fairly high level of geographic detail. Land area available for development is inventoried by general comprehensive plan category for each TAZ. The model then continually uses and updates this inventory as developments are sited.

The basic process in LUSDR are as follows:

1) A synthetic population of households is generated from a forecast of population by age cohort. Joint probabilities of a person belonging to a household of each combination of size, workers and age of head categories by age cohort are used to create a household type for each person in each age cohort. These are converted into households by dividing by average household size for each size category. Household income, tenure, and dwelling type are added successively to the household records using terminal node probabilities of decision trees. The steps are shown in more detail in Figure 4.

2) Total employment is forecast from total household workers and the ratio of employment to workers in the region. The employment is split into employment sectors and employment clusters using joint probabilities derived from employment and property data. Employment sectors are partitioned based on 2-digit NAICS classifications with the variation that the accommodations sector is split into restaurants and other accommodations. Employment clusters represent how establishments group together into developments such as shopping centers. These clusters were identified through analysis of employment data, tax lot data, building footprint data, and aerial photos. Cluster analysis was used to identify a clustering typology. Establishments are aggregated from the employment in each category using the employment size distributions (numbers of employees) derived from the employment data. For some sectors, the establishment size distribution differs if the establishment is located in a cluster of different types (multitype) or if the establishment is located by itself or with other establishments of the same type (monotype). The steps are shown in more detail in Figure 5.

3) Residential developments are generated from the synthetic households by aggregating households of like type into developments of various sizes. Developments are creating by successively drawing from development size distributions and then randomly assigning households of the same type to the development. Size distributions were derived from local partition and subdivision data, Census data on units in residential buildings, tax lot data, and building footprint data. Residential developments are randomly assigned to development periods.

The developments are assigned with a land needs requirement and a unit land price. The land needs requirements per household by development type and unit land prices were estimated from tax lot data. The total needs are estimated by multiplying the household unit needs by the number of households and a factor to convert net acres to gross acres (to account for infrastructure needs). The steps are shown in more detail in Figure 6.

4) Business developments are generated by aggregating employment establishments into clusters. Clusters are generated by successively drawing from cluster size distributions and then randomly assigning employment establishments having the identified cluster type. The cluster size distributions were derived from the combination of employment, tax lot, building footprint and aerial photo data. Business developments are randomly assigned to development periods. Business developments are also clustered into various location types. This was done to reduce the number of classes and increase the data available for estimating location preference models. The developments are assigned with a land needs requirement and a unit land price. The land needs requirements per employee by development type and unit land prices were estimated from tax lot data. The total needs are estimated by multiplying the employee needs by the number of employees and a factor to convert net acres to gross acres (to account for infrastructure needs). The steps are shown in more detail in Figure 7.

5) The developments are allocated for each period. The allocation is based on consideration of land constraints, including environmental and regulatory constraints, location preferences, and prices. Neighborhood and regional accessibilities in the location preference models are the main interaction between transportation and land use. These accessibilities are updated at the end of allocating development for the period. The updated accessibilities then inform the probabilities for the next period. To date, the transportation model is not being rerun at the end of each period to get new travel times, but that could be done. Within each period, developments are allocated to TAZs in two iterating steps. In the first step, each development is allocated to a TAZ based on consideration of constraints and preferences. The steps are shown in more detail in Figure 8.

> a) In the constraints step, a set of candidate TAZs is developed. The first part of this process is to determine whether the development will be located in an urban or rural areas. Developments that can be located in rural areas include single-family and mobile home partitions and subdivisions having 20 or fewer lots and agriculture-forestry sector employment establishments. (In addition mining employment is allocated only to existing TAZs that current have mining. All are rural.) A development of one of these types locates in a rural vs. urban area is done through a random draw where the probabilities are calculated from the respective urban and rural areas in the model area, weighted by the compatibility of the development type with the area designations. For rural developments, candidate TAZs are identified as those having an unconstrained land area that equals or exceeds the land needs of the development. For urban developments, candidate TAZs are identified as those having a weighted area that equals or exceeds the land needs of the development. The weighted area of a TAZ is calculated by multiplying the land area in each plan category in the TAZ by the compatibilities of the development type with the respective categories and summing the result.

b) A choice of TAZ is made from the set of candidate TAZs using a binomial regression model that predicts the probability that the development type is present in the TAZ. The probabilities calculated from the model serve as the weights for the random draw. Regression models were developed for all of the development location types. In the case of residential developments, the location types are the same as the development types. For business developments, the cluster types were partitioned into eight groupings to determine location. (These are described in more detail below.)

The full set of variables in the regression model are: slope, steep slope, distance to interchange, traffic exposure, local accessibility to employment, regional accesssibility to employment, local accessibility to households, and regional accessibility to households. The variables are not all significant for all of the location types. They are included in the models where they were found to be significant. The steep slope variable was added after the models were estimated to keep development off steeper land. The slope variable did not do an adequate job of this because of insufficient data on development on steeper land. The traffic exposure variable is a measure of the potential exposure to traffic rather than actual traffic volumes. It is basically a measure of the number of OD paths that are in the vicinity of each TAZ. The local and regional accessibilities are calculated with one formulation, an exponential distance decay relationship where the decay for the local accessibility is greater than for the regional accessibility.

c) Once all of the developments have been allocated to TAZs, LUSDR checks that there is sufficient land available in each TAZ to accommodate all of the developments. Where land supply is insufficient, a bidding process is followed to determine which developments are successfully sited and which are not. The bidding uses the unit land prices for each development type.

The bidding process is done by plan category within each TAZ. It starts with identifying the plan categories that each development may locate in. This is done as a random draw using the plan compatibilities as weights for each each plan category. The list of eligible categories for each development are then ordered in descending order of plan compatibility. Supply and demand are balanced by working through this order of choices for all the developments. So for example, starting with the first choice of all developments, a comparison is made for each plan category represented in these choices. Allocation in each plan category proceeds interatively. The largest development that has the highest unit land price is allocated the space in each iteration. The space used is removed from the inventory and interation proceeds likewise until no developments can fit within the remaining area. Developments successfully sited are removed from the list of developments to be sited. Developments not successfully sited are then attempted to be sited in their second choice plan category in the same way. Developments that cannot be sited through this process are combined into a list of developments that need to got back through the whole siting process.

Figure 4
Processes for Creating Households

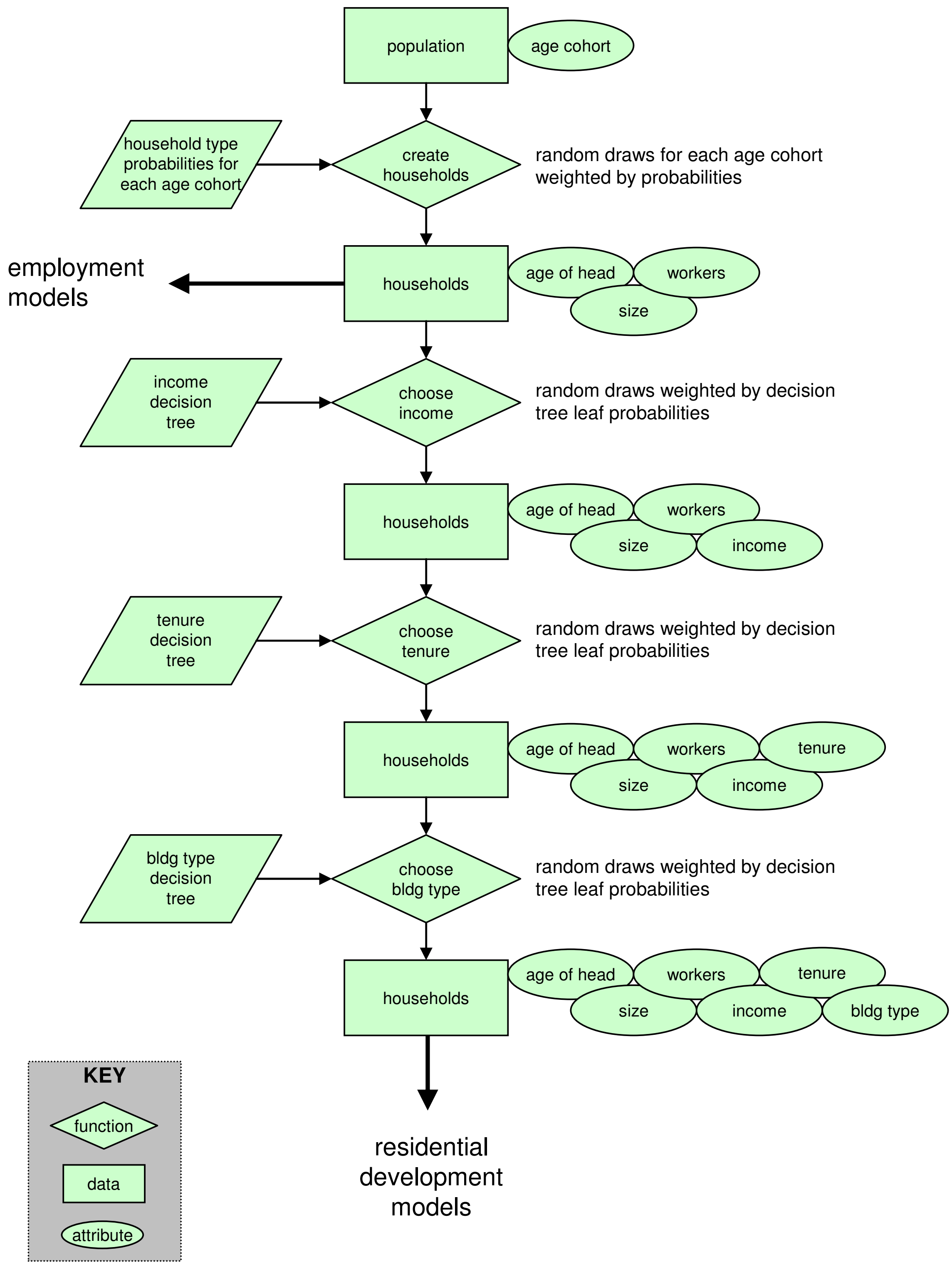


Figure 5
Processes for Creating Employment Establishments

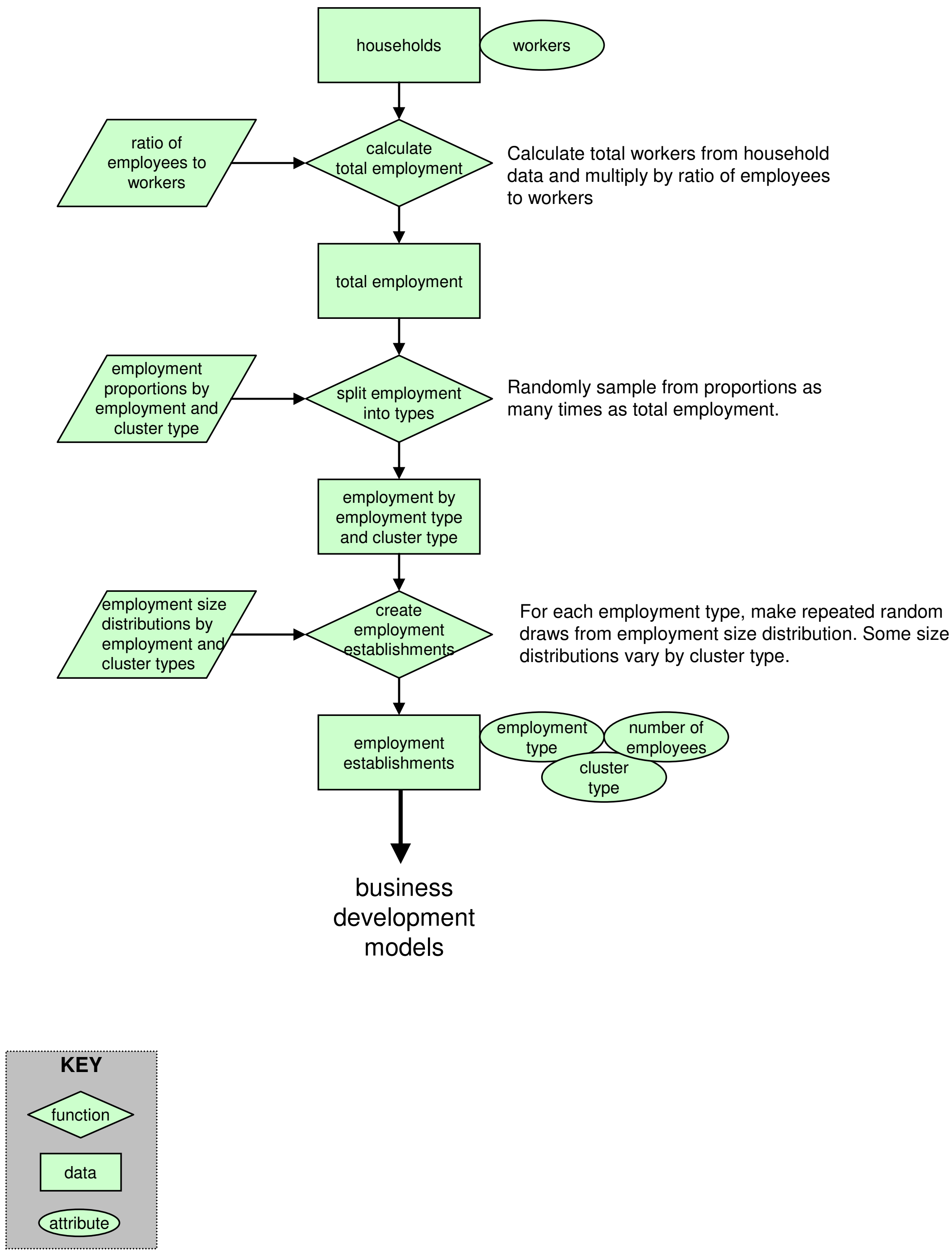
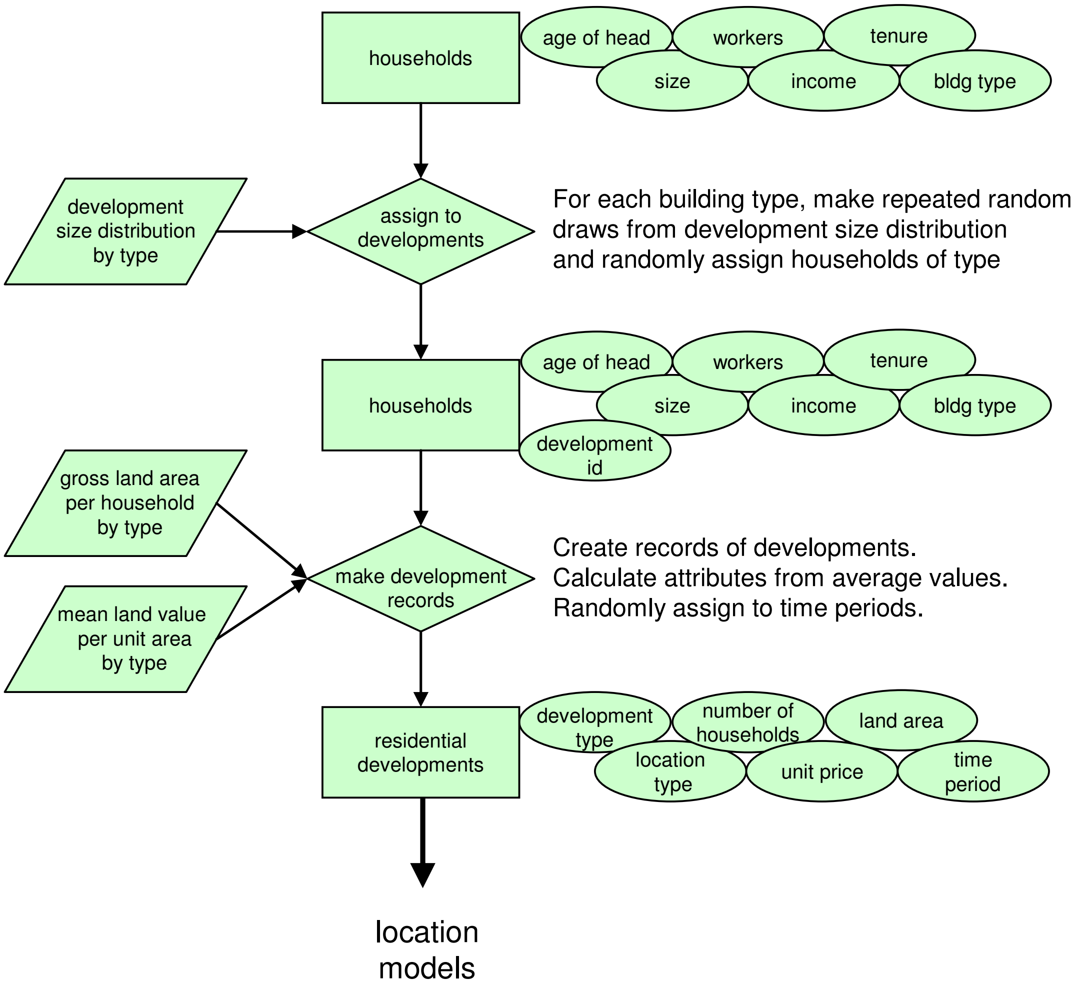


Figure 6
Processes for Creating Residential Developments



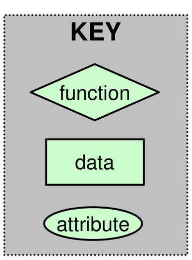


Figure 7
Processes for Creating Business Developments

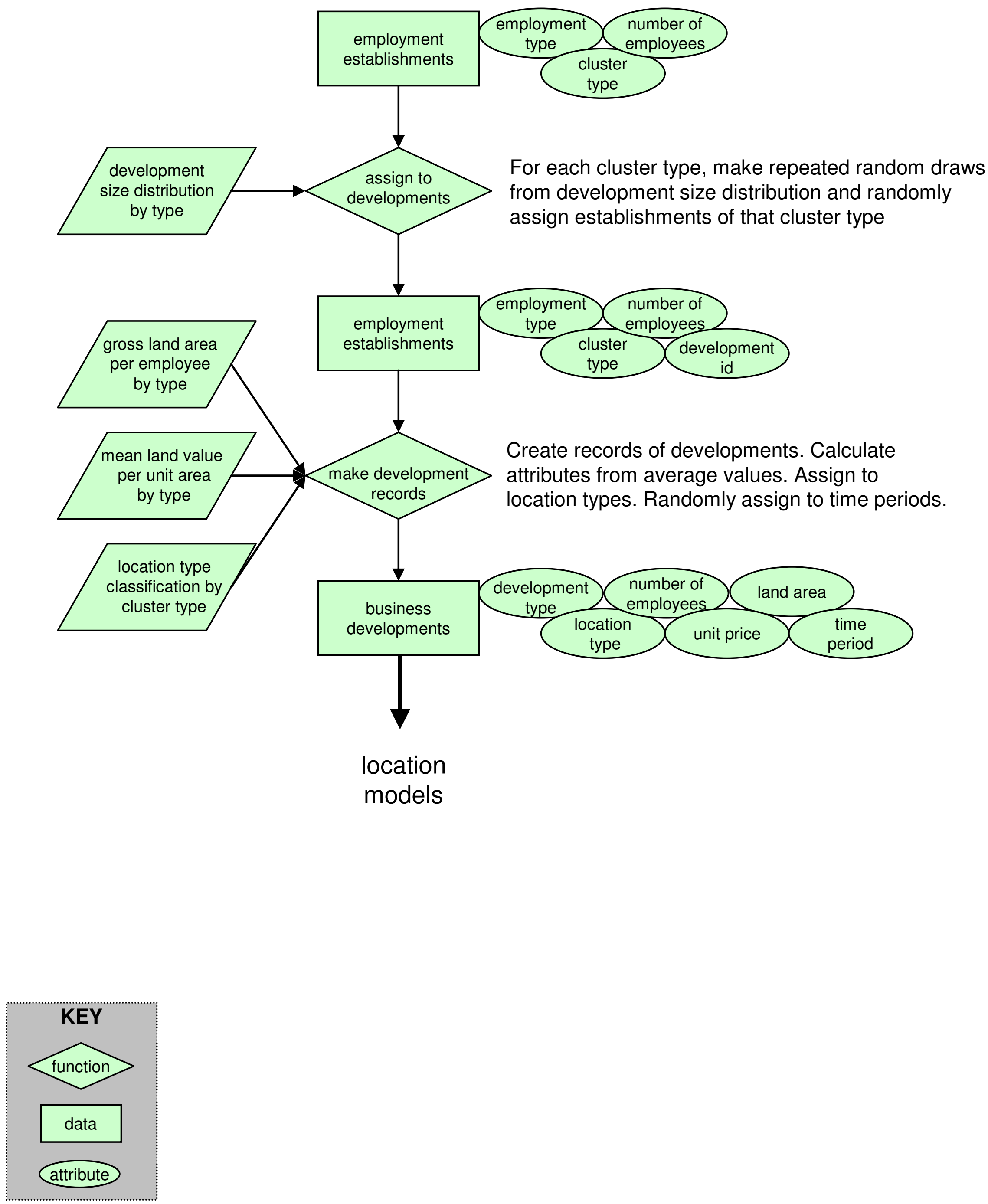
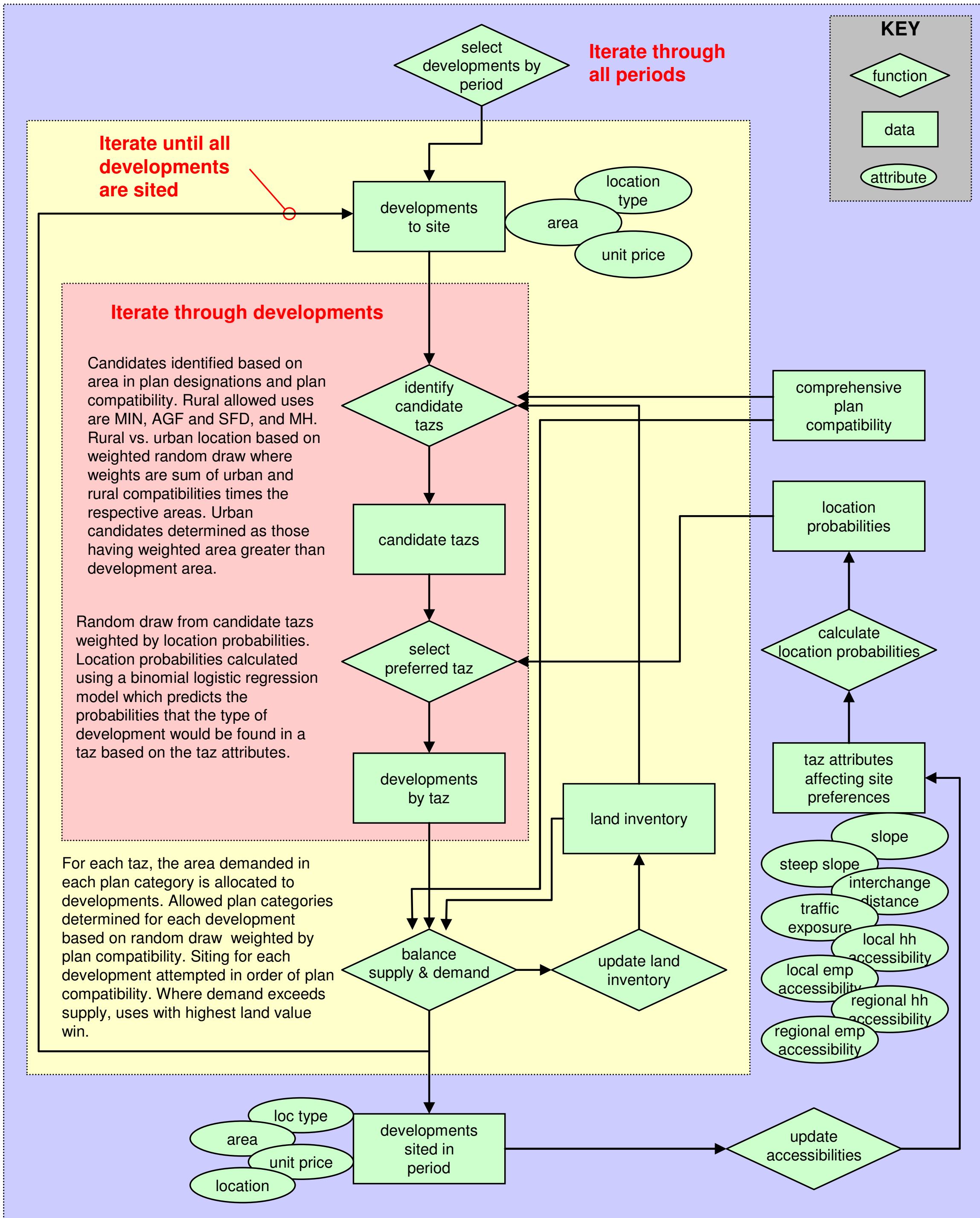


Figure 8
Processes for Locating Developments



Estimation and Calibration of the Household and Residential Development Models

Following are the steps in a the model to produce future households and groupings of them into residential developments.

It was desired to have the household models be sensitive to changing age demographics. The state demographer produces long-range forecasts of people by age cohort for each county. These forecasts are converted into proportions of the population by age cohort and then multiplied by the target population to calculate the target population by age cohort.

The most straighforward way thought of to generate households from population age cohorts was to develop a cross-tabulation of population by household size category, worker category, and age of household head category for each population age cohort from PUMS data. The size, worker and age of head categories follow the categorization scheme used in the joint estimated metropolitan area models. The PUMS person data for Jackson County were joined with the corresponding data for the household each person is in. Each person record was weighted with the corresponding household weight. Household weights were calculating by iterative proportional fitting the cross-tabulation of household size, worker and age-of-head characteristics with Census marginal distributions of each characteristic. The cross-tabulations of persons by household type for each age cohort were converted into joint probabilities. These joint probabilities are used by the model in a Monte Carlo process to create an array of persons by household category. This array is then divided across the household size dimension by the average household size of each category to produce an array of households by size, workers and age-of-head. This array is converted into a list of individual households by each of the characteristics. Table 1 compares household size percentages estimated using the model for 1990 and 2000 for Jackson County populations with Census percentages. Table 2 likewise compares worker percentages. Table 3 compares the estimated and observed joint household size and worker percentages for 1990 and 2000. Table 4 compares observed and estimated age of household head percentages.

Table 1
Comparison of Observed and Estimated Household Size Percentages

Size Categories	1990 Census	1990 Estimated	2000 Census	2000 Estimated
1 person	23.9	24.8	25.1	24.8
2 persons	38.0	38.3	37.8	38.5
3 persons	15.6	15.8	15.3	15.8
4+ persons	22.5	21.1	21.9	20.9

Table 2
Comparison of Observed and Estimated Household Worker Percentages

Size Categories	1990 Census	1990 Estimated	2000 Census	2000 Estimated
0 worker	33.4	30.3	31.3	30.6
1 worker	33.7	35.5	35.0	35.3
2 workers	27.6	28.6	28.3	28.5
3+ workers	5.3	5.6	5.4	5.6

Table 3
Comparison of Observed and Estimated Joint Household Size and Worker Percentages
1990 and 2000

	1990 estimated (observed)			
	1 person	2 persons	3 persons	4 persons
0 worker	14.1 (14.2)	10.6 (9.7)	0 (0)	0 (0)
1 worker	14.0 (15.4)	11.4 (11.7)	12.9 (11.7)	0 (0)
2 workers	1.3 (1.9)	5.8 (5.4)	6.9 (6.4)	1.8 (1.9)
3+ workers	0.9 (1.9)	7.6 (7.9)	8.8 (9.4)	3.8 (3.4)
	2000 estimated (observed)			
	1 person	2 persons	3 persons	4 persons
0 worker	14.2 (14.5)	10.6 (10.6)	0 (0)	0 (0)
1 worker	14.2 (13.9)	11.5 (11.3)	12.8 (12.5)	0 (0)
2 workers	1.2 (1.5)	5.8 (5.8)	6.9 (6.4)	1.9 (1.6)
3+ workers	0.9 (1.3)	7.5 (7.3)	8.8 (9.4)	3.7 (3.8)

Table 4
Comparison of Observed and Estimated Age of Household Head Percentages

Size Categories	1990 Census	1990 Estimated	2000 Census	2000 Estimated
0 worker	4.9	6.7	5.7	6.6
1 worker	55.2	54.6	53.6	54.3
2 workers	13.7	13.9	14.7	14.1
3+ workers	26.2	24.8	26.0	25.2

Serveral decision trees are used to add income, tenure and building type characteristics to the household records. The decision trees were estimated using PUMS household data. The PUMS data for Jackson County was used to estimate tenure and building type. It was necessary, however, to use the PUMS data for all of Oregon to produce a satisfactory result for the income. tree. Estimation of the trees was done using the "party" package for R. Party uses a recursive partitioning approach, but the criteria by which partitions are made is unique to this package.

Most tree methods use information gain tests for partitioning. Party uses conditional inference. One result of this is that the statistical significance of each partitioning is calculated. The trees for income, tenure and building type are shown in Figures 9, 10, and 11 respectively. The "p values" for each split are shown in the trees. The terminal nodes of the trees show the distribution of cases in each category for households classified in the respective nodes. These distributions are used in a Monte Carlo process to select the characteristics for the households. Table 5 compares observed and estimated income percentages for 1990 and 2000. Tables 6 and 7 compare observed and estimated tenure and building types respectively. The model does a very good job predicting all attributes except income. The prediction of income is acceptable and does not detract from the prediction of tenure or building type. Note that the income numbers for 1990 are not adjusted for inflation, hence the downward shift in the percentages relative to the estimated values.

Table 5
Comparison of Observed and Estimated Household Incomes

Income Categories	1990 Census (1990 dollars)	1990 Estimated (2000 dollars)	2000 Census (2000 dollars)	2000 Estimated (2000 dollars)
0 – 15K	25.0	19.0	17.3	18.9
15K – 30K	30.7	27.6	23.1	27.4
30K – 45K	23.7	20.9	19.8	21.0
45K – 60K	11.4	12.7	13.8	12.8
60K +	9.2	19.8	25.9	19.8

Table 6
Comparison of Observed and Estimated Household Tenure

Tenure Categories	1990 Census	1990 Estimated	2000 Census	2000 Estimated
Own	66.2	64.8	66.5	64.9
Rent	33.8	35.2	33.5	35.1

Table 7
Comparison of Observed and Estimated Household Building Types

Building Type Categories	1990 Census	1990 Estimated	2000 Census	2000 Estimated
Single Family Detached	63.9	63.7	63.9	63.8
Single Family Attached	2.2	3.1	2.2	3.1
2-4 Unit Apartment	7.6	8.0	8.3	7.7
5+ Unit Apartment	8.0	8.7	9.3	8.6
Mobile Home	17.5	16.0	14.9	16.4
Other	0.8	0.4	0.5	0.4

The building types that households occupy were converted in to development types. The building types used follow categories of the Census (with some collapsing of categories).

- Single family detached
- Mobile (Manufactured) home
- Apartment with 2-4 units
- Apartment with more than 4 units
- Single family attached

The single family detached category was split based on the household income. The highest income households with this type were classified as single family detached high income (SFDH). The other income category households with this type were classified at single family detached moderate income (SFDM). The category of apartments with 2-4 units was combined with the SFDM because duplexes, triplexes and quadplexes are often interspersed in subdivisions that are predominantly single family dwellings. The manufactured homes were split into manufactured homes in subdivisions and manufactured homes in parks. This was done as a result of analyzing a building footprint geographic coverage in relation to tax lot maps and aerial photos. Thresholds were developed for identifying whether a manufactured home is in a park vs. a lot based on the size of the property and the number of buildings. This was used to calculate the proportion of manufactured homes in parks. The proportion is used by the model using a Monte Carlo process to assign manufactured homes to parks vs. individual lots. Single family attached buildings were unaltered, but were considered to be condominiums.

Once the development types are identified, the households can be grouped into corresponding developments. This is done by drawing from development size distributions. To derive these distributions (and to identify employment clusters) it was necessary to analyze the tax lot and buildings footprint geographic date to identify properties. Taxlots are joined into properties that attempt to define groupings of properties that describe developments (for example a shopping center or office park). Groupings were made through a combination of spatial methods and visual examination of development patterns using the following rules:

1. taxlots occupied by a building were combined into a property
2. taxlots that were enclosed by another taxlot were combined with the enclosing taxlot into a property
3. adjacent taxlots having the same owner and a compatible development type were combined into a property
4. on visual examination (aerial photos), taxlots that appeared to be one development were combined
5. in a few cases, groups of taxlots were combined where it appeared that they may have been part of the same plat and where employment geocoding appeared to overallocate employment to some buildings and to underallocate it to others.

The property information was used in conjunction with Census data on number of units in apartment buildings to develop development size distributions for apartments.

The size distribution for condominiums was developed using the property data since each condominium in a development has a corresponding tax lot record.

The distribution of mobile home park sizes was developed by counting buildings from the footprint geographic coverage on mobile home park properties.

The distribution of single family partition and subdivision sizes was developed from records from several local governments of subdivisions and partitions over the past five years. (Not all local governments chose to participate.) The same size distribution is used for manufactured homes on lots.

Residential development sizes are chosen from distributions derived from the inventory data using in intermediate “smoothing” process. The log of size (number of households) is used as the variable because size tends to follow either a lognormal or power distribution. To make a choice of development size, the actual distribution for the respective development type is smoothed by creating a histogram from the inventory data and then fitting fourth-order splines to the histogram midpoints. The smoothed distribution is then used to sample from to create developments of different sizes.

Figure 9
Household Income Decision Tree

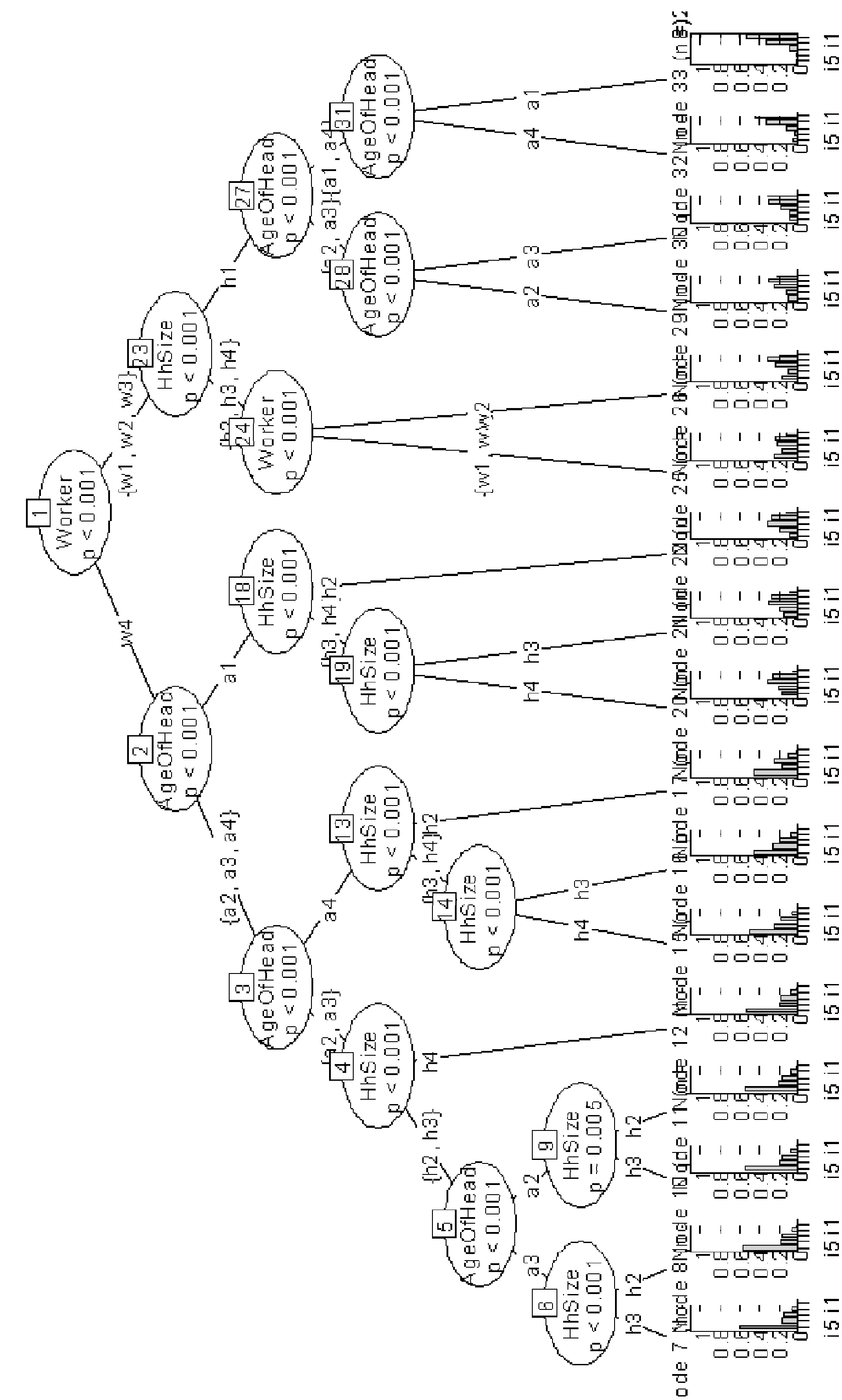


Figure 10
Tenure Decision Tree

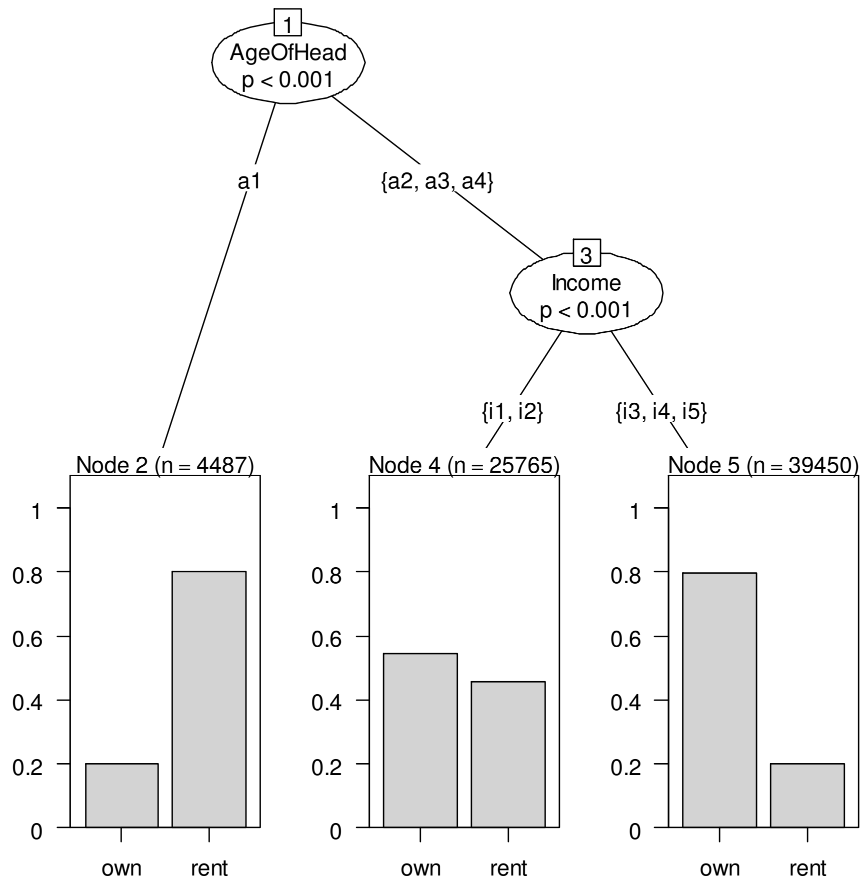
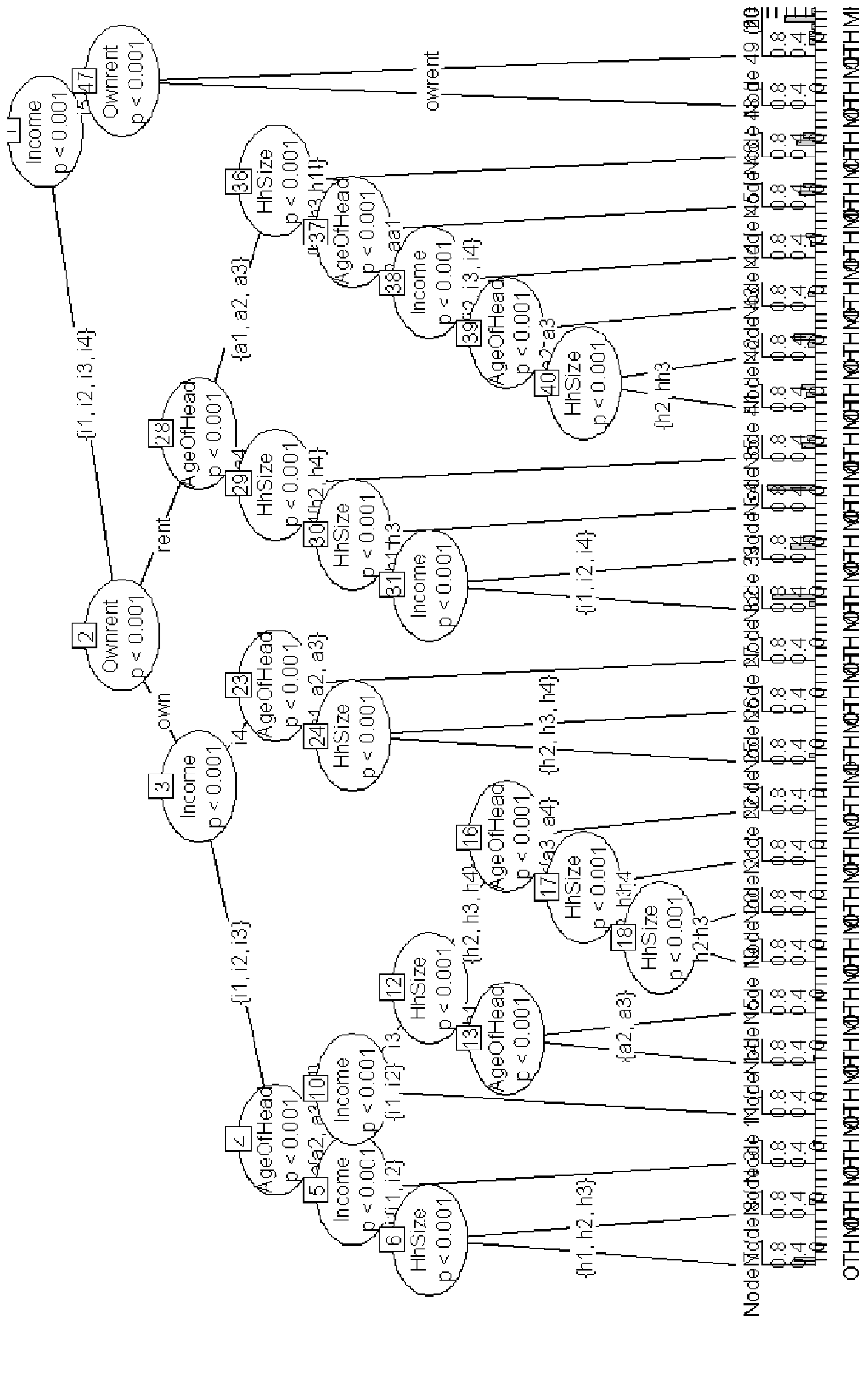


Figure 11
Building Type Decision Tree



Estimation and Calibration of the Employment Establishment and Business Development Models

Following are the steps in a the model to produce future employment establishments and groupings of them into business developments.

Workers are generated in the household model. Employment is established as workers multiplied by a constant. This is determined from the current ratio of employment to workers in the model area.

Employment is allocated to employment type (2-digit NAICS) and cluster types based on joint probabilities derived from present distributions. Clusters are groups of dissimilar employment types that commonly locate in the same development. The process used for identifying these clusters is described below. The joint probabilities are used to allocate employment to types using a Monte Carlo process. Figure 12 shows the joint probabilities.

Employment by employment type is split into establishments by drawing from distributions of establishment size (numbers of employees) by employment and cluster type. The employment size distribution for some employment types varies based on whether the employment establishment is located in a multitype cluster or whether it is alone or with similar types. For example, education establishments that are located alone with other education establishments tend to be larger than education establishments that are located with other types of establishments. Non-parametric tests (Kolmogorov-Smirnov, and Wilcox Mann Whitney) were performed to identify those employment types that have significantly different size distribution whether they are in monotype or multitype clusters. The results are shown in Figure 13.

The selection of employment establishment size is made by LUSDR in the same way that residential development sizes are chosen (see above). Figure 14 shows that this process does a reasonable job of replicating existing size distributions.

After a list of business establishments have been created by employment type and cluster type, they are grouped into clusters. The grouping is done in the same way that households are allocated to residential developments. Developments are created by random draw from a distribution of sizes for the appropriate cluster type. In this case, the size of the cluster is represented by the number of establishments. The size distributions are smoothed in the same way as described above. Establishments of identified as being of that cluster type are then randomly selected to locate in the cluster. This process is done repeatedly until all establishments of a cluster type have been located in a cluster.

Figure 12
Joint Probabilities of Employment Type and Cluster Type

	ACC	ADM	AGF	CNS	EDU	FIN	FIN_CLUST	HLH	HLH_CLUST	INF
ACC	0.00905	0	0	0	0	0	0	0	0	0
ADM	0	0.01578	0	0	0	0	0.00089	0	0.00478	0
AGF	0	0	0.02041	0	0	0	0.00003	0	0.00001	0
CNS	0	0	0	0.0309	0	0	0.00058	0	0.00039	0
EDU	0	0	0	0	0.04417	0	0.00036	0	0.00052	0
FIN	0	0	0	0	0	0.01053	0.01013	0	0.00145	0
HLH	0	0	0	0	0	0	0.00093	0.05611	0.07862	0
INF	0	0	0	0	0	0	0.0008	0	0.00039	0.01462
MFG	0	0	0	0	0	0	0.00031	0	0.00099	0
MIN	0	0	0	0	0	0	0	0	0	0
MNG	0	0	0	0	0	0	0.00456	0	0.00291	0
OSV	0	0	0	0	0	0	0.00064	0	0.00022	0
PRF	0	0	0	0	0	0	0.00276	0	0.00341	0
PUB	0	0	0	0	0	0	0.0015	0	0.00196	0
REC	0	0	0	0	0	0	0.00116	0	0.00007	0
REL	0	0	0	0	0	0	0.00033	0	0.00052	0
RST	0	0	0	0	0	0	0.00051	0	0.00055	0
RTL	0	0	0	0	0	0	0.00006	0	0.00028	0
TRN	0	0	0	0	0	0	0.0002	0	0.0001	0
UTL	0	0	0	0	0	0	0	0	0	0
WHL	0	0	0	0	0	0	0.00118	0	0.00012	0

	MFG	MFG_CLUST	MIN	MNG	OSV	OSV_CLUST	PRF	PRF_CLUST	PUB	REC
ACC	0	0.00089	0	0	0	0.00003	0	0.0001	0	0
ADM	0	0.01571	0	0	0	0	0	0.00153	0	0
AGF	0	0.00145	0	0	0	0.0001	0	0.00006	0	0
CNS	0	0.01186	0	0	0	0.0002	0	0.00045	0	0
EDU	0	0.01451	0	0	0	0.00732	0	0.00006	0	0
FIN	0	0.00032	0	0	0	0.00036	0	0.00048	0	0
HLH	0	0.00068	0	0	0	0.00381	0	0.00004	0	0
INF	0	0.00219	0	0	0	0.00087	0	0	0	0
MFG	0.05787	0.02887	0	0	0	0	0	0.00565	0	0
MIN	0	0	0.00123	0	0	0	0	0	0	0
MNG	0	0.00214	0	0.00263	0	0	0	0	0	0
OSV	0	0.00224	0	0	0.02121	0.00325	0	0.00026	0	0
PRF	0	0.0008	0	0	0	0.00033	0.01037	0.00469	0	0
PUB	0	0.01267	0	0	0	0.00004	0	0.0001	0.03201	0
REC	0	0.00279	0	0	0	0.00084	0	0	0	0.0077
REL	0	0.00119	0	0	0	0.00062	0	0.00078	0	0
RST	0	0.00121	0	0	0	0.00001	0	0.00026	0	0
RTL	0	0.00404	0	0	0	0.00029	0	0	0	0
TRN	0	0.00802	0	0	0	0	0	0.00009	0	0
UTL	0	0.00243	0	0	0	0	0	0	0	0
WHL	0	0.00192	0	0	0	0.00061	0	0	0	0

Figure 12 Continued
Joint Probabilities of Employment Type and Cluster Type

	REL	RST	RST_CLUST	RTL	RTL_CLUST	TRN	UTL	WHL	WHL_CLUST
ACC	0	0	0.0018	0	0.00058	0	0	0	0
ADM	0	0	0.00041	0	0.00427	0	0	0	0.00048
AGF	0	0	0.00015	0	0.00293	0	0	0	0.00369
CNS	0	0	0	0	0.0016	0	0	0	0.00086
EDU	0	0	0.00003	0	0.00115	0	0	0	0
FIN	0	0	0.00076	0	0.00504	0	0	0	0
HLH	0	0	0.00141	0	0.00767	0	0	0	0.00015
INF	0	0	0.00022	0	0.00663	0	0	0	0
MFG	0	0	0.00058	0	0.00108	0	0	0	0.00041
MIN	0	0	0	0	0	0	0	0	0
MNG	0	0	0.00013	0	0.00224	0	0	0	0
OSV	0	0	0.00064	0	0.00648	0	0	0	0.0002
PRF	0	0	0	0	0.0033	0	0	0	0.00045
PUB	0	0	0.00003	0	0.00372	0	0	0	0
REC	0	0	0.00615	0	0.00193	0	0	0	0
REL	0.00898	0	0.00023	0	0.00279	0	0	0	0.0006
RST	0	0.03111	0.01191	0	0.03557	0	0	0	0
RTL	0	0	0.00017	0.04767	0.12682	0	0	0	0.00017
TRN	0	0	0.00013	0	0.00513	0.02097	0	0	0.00031
UTL	0	0	0	0	0	0	0.00256	0	0
WHL	0	0	0.00089	0	0.00632	0	0	0.01835	0.0042

ACC = Accommodations
ADM = Administration
AGF = Agriculture and Forestry
CNS = Construction
EDU = Education
FIN = Finance
HLH = Health
INF = Information
MFG = Manufacturing
MIN = Mining
MNG = Management
OSV = Other Services
PRF = Professional
PUB = Public
REC = Recreation
REL = Real Estate
RST = Restaurant
RTL = Retail
TRN = Transportation
UTL = Utilities
WHL = Wholesale

Figure 13

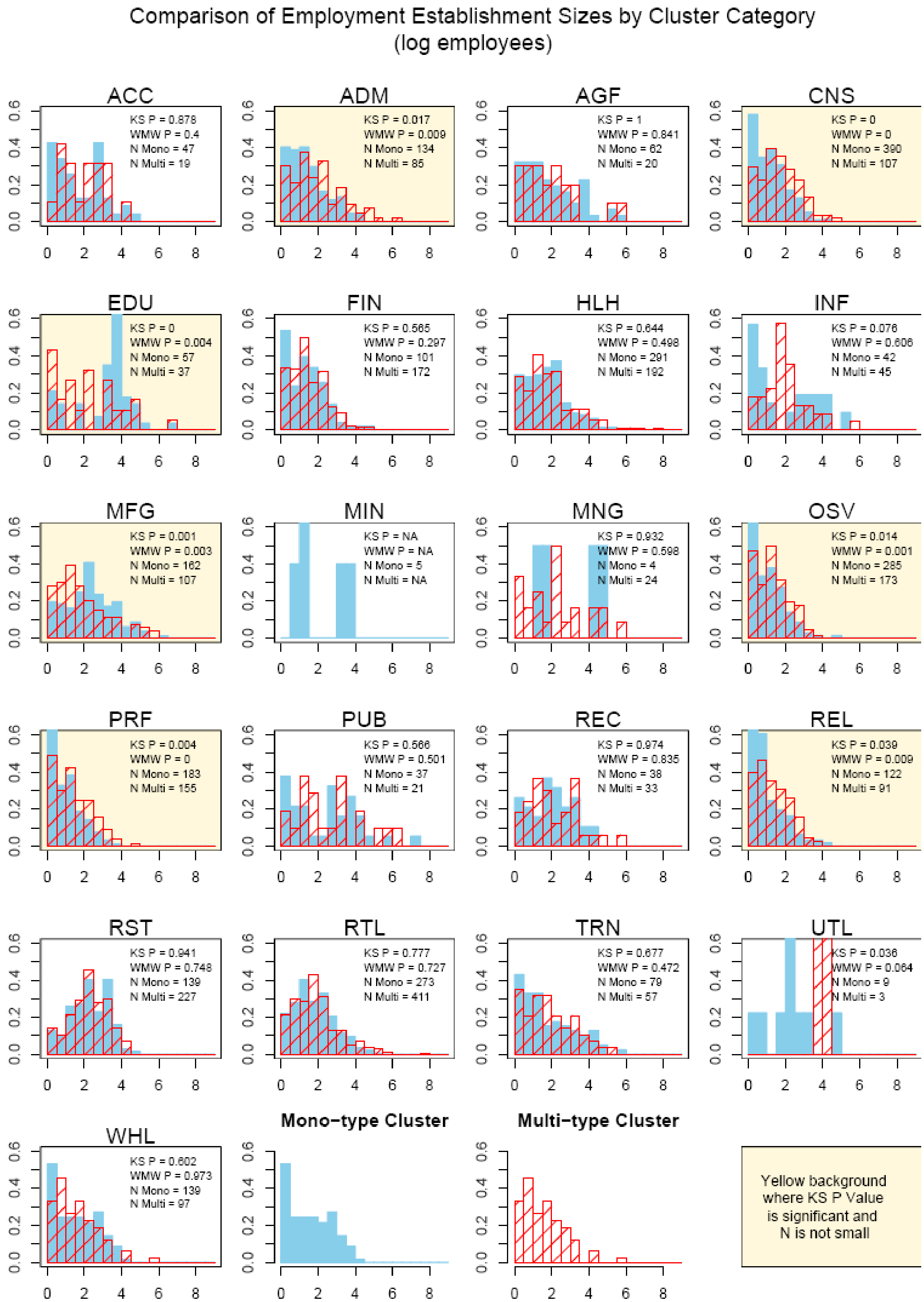
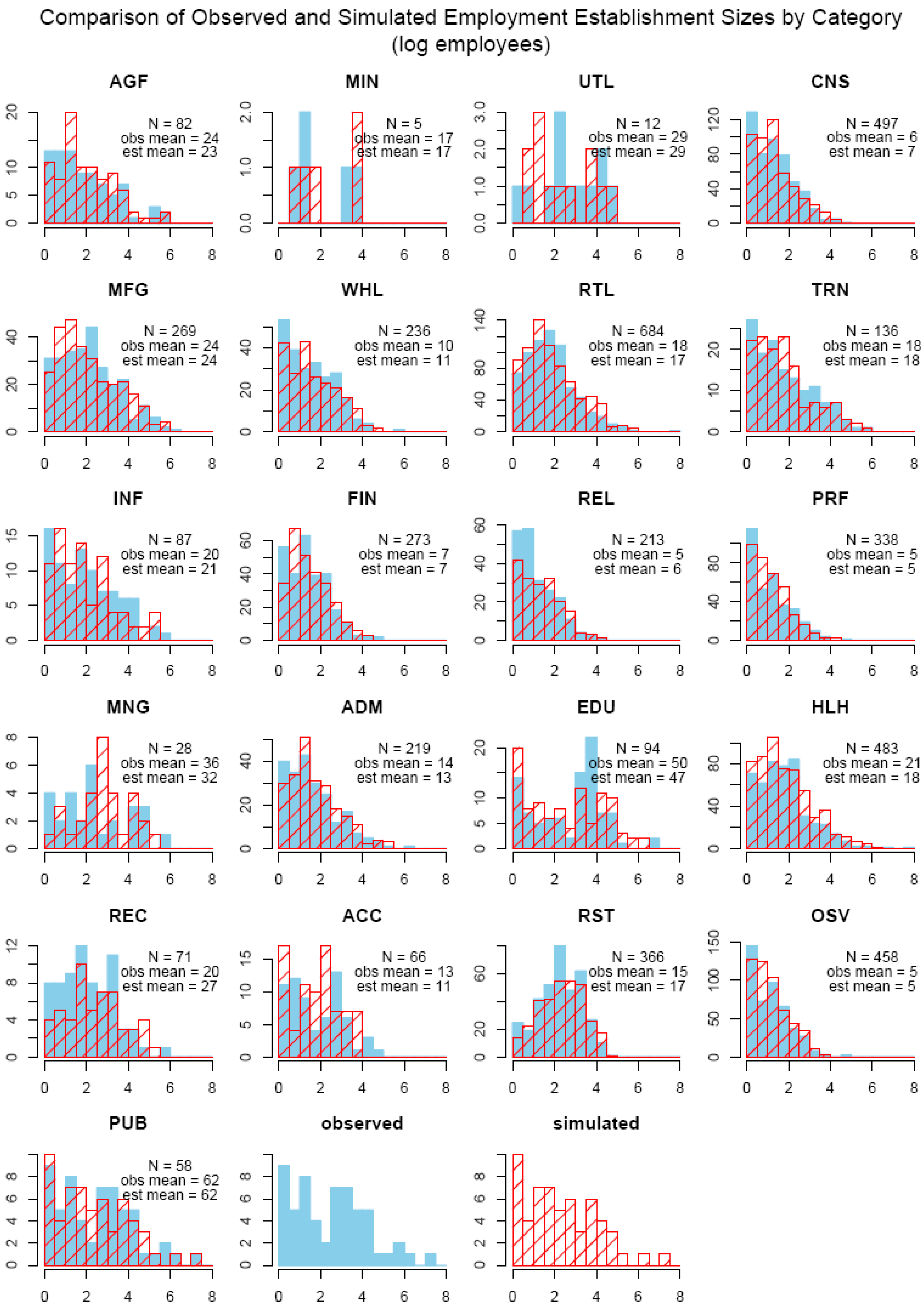

Comparison of Employment Establishment Sizes by Cluster Category
(log employees)
ACC
KS P = 0.878
WMW P = 0.4
N Mono = 47
N Multi = 19
ADM
KS P = 0.017
WMW P = 0.009
N Mono = 134
N Multi = 85
AGF
KS P = 1
WMW P = 0.841
N Mono = 62
N Multi = 20
CNS
KS P = 0
WMW P = 0
N Mono = 390
N Multi = 107
EDU
KS P = 0
WMW P = 0.004
N Mono = 57
N Multi = 37
FIN
KS P = 0.565
WMW P = 0.297
N Mono = 101
N Multi = 172
HLH
KS P = 0.644
WMW P = 0.498
N Mono = 291
N Multi = 192
INF
KS P = 0.076
WMW P = 0.606
N Mono = 42
N Multi = 45
MFG
KS P = 0.001
WMW P = 0.003
N Mono = 162
N Multi = 107
MIN
KS P = NA
WMW P = NA
N Mono = 5
N Multi = NA
MNG
KS P = 0.932
WMW P = 0.598
N Mono = 4
N Multi = 24
OSV
KS P = 0.014
WMW P = 0.001
N Mono = 285
N Multi = 173
PRF
KS P = 0.004
WMW P = 0
N Mono = 183
N Multi = 155
PUB
KS P = 0.566
WMW P = 0.501
N Mono = 37
N Multi = 21
REC
KS P = 0.974
WMW P = 0.835
N Mono = 38
N Multi = 33
REL
KS P = 0.039
WMW P = 0.009
N Mono = 122
N Multi = 91
RST
KS P = 0.941
WMW P = 0.748
N Mono = 139
N Multi = 227
RTL
KS P = 0.777
WMW P = 0.727
N Mono = 273
N Multi = 411
TRN
KS P = 0.677
WMW P = 0.472
N Mono = 79
N Multi = 57
UTL
KS P = 0.036
WMW P = 0.064
N Mono = 9
N Multi = 3
WHL
KS P = 0.602
WMW P = 0.973
N Mono = 139
N Multi = 97
Mono−type Cluster
Multi−type Cluster
Yellow background
where KS P Value
is significant and
N is not small

Figure 14


Comparison of Observed and Simulated Employment Establishment Sizes by Category
(log employees)
AGF
N = 82
obs mean = 24
est mean = 23
MIN
N = 5
obs mean = 17
est mean = 17
UTL
N = 12
obs mean = 29
est mean = 29
CNS
N = 497
obs mean = 6
est mean = 7
MFG
N = 269
obs mean = 24
est mean = 24
WHL
N = 236
obs mean = 10
est mean = 11
RTL
N = 684
obs mean = 18
est mean = 17
TRN
N = 136
obs mean = 18
est mean = 18
INF
N = 87
obs mean = 20
est mean = 21
FIN
N = 273
obs mean = 7
est mean = 7
REL
N = 213
obs mean = 5
est mean = 6
PRF
N = 338
obs mean = 5
est mean = 5
MNG
N = 28
obs mean = 36
est mean = 32
ADM
N = 219
obs mean = 14
est mean = 13
EDU
N = 94
obs mean = 50
est mean = 47
HLH
N = 483
obs mean = 21
est mean = 18
REC
N = 71
obs mean = 20
est mean = 27
ACC
N = 66
obs mean = 13
est mean = 11
RST
N = 366
obs mean = 15
est mean = 17
OSV
N = 458
obs mean = 5
est mean = 5
PUB
N = 58
obs mean = 62
est mean = 62
observed
simulated

Identifying a Typology of Business Developments

Taxlots are joined into properties that attempt to define groupings of properties that describe developments (for example a shopping center or office park). Groupings were made through a combination of spatial methods and visual examination of development patterns using the following rules:

1. taxlots occupied by a building were combined into a property
2. taxlots that were enclosed by another taxlot were combined with the enclosing taxlot into a property
3. adjacent taxlots having the same owner and a compatible development type were combined into a property
4. on visual examination (aerial photos), taxlots that appeared to be one development were combined
5. in a few cases, groups of taxlots were combined where it appeared that they may have been part of the same plat and where employment geocoding appeared to overallocate employment to some buildings and to underallocate it to others.

Cluster analysis was used to group employment establishments located on the same property into cluster types. Various hierarchical clustering methods available in R were tried. These included methods available in the cluster package and the hclust function in the stats package. The methods in the cluster package are from Kaufman and Rousseeuw (1990). Hclust is from F. Murtagh (1985).

The first step was to separate the employment establishment data on the basis of whether an establishment is by itself, whether it is part of a group of establishments all of the same type, and whether it is part of a group of establishments of different types. Cluster analysis was performed on the cases where establishments were in groups of multiple types.

Cluster analysis uses measures of "distance" between cases to identify clusters. Typically distance is measured along many dimensions. The variables chosen to test clustering on were employment of each type and employment establishments of each type. Normalization among the variables is often necessary in order to form meaningful clusters. Normalization was accomplished by using the percentages of employment by type and percentages of employment establishments by type respectively. Various methods are available for calculating a distance measurement across multiple dimensions. The most common of these is Euclidean. This was tried as well as three others after the best clustering methods and variables were determined. Following is a summary of the clustering tests and the results in the form of the number of cases in each cluster. All tests shown are for the creation of 8 clusters. This number of clusters is a compromise between establishing variation in cluster types and having enough cases in each cluster.

Function	Variable	Method	Number of Cases in Each Cluster							
agnes	emp pct	euclidean	354	28	36	38	5	7	11	2
agnes	est pct	euclidean	187	119	105	43	5	12	4	6
diana	emp pct	euclidean	106	120	22	9	127	89	6	2
diana	est pct	euclidean	38	51	37	50	31	147	29	98
hclust	emp pct	euclidean	38	7	35	12	2	10	36	341
hclust	est pct	euclidean	36	31	24	26	40	148	41	135
hclust	est pct	manhattan	1	3	7	12	32	4	18	404
hclust	est pct	maximum	20	87	67	16	11	17	14	249
hclust	est pct	minkowski	37	31	20	31	40	148	40	134

Notice that the size of clusters is very unbalanced in the cases where percentage of employment is used as the clusting variable. In these instances, there are some clusters that are large and some that are very small. Clustering based on the percentage of establishments produces more even size distributions. From these results, the decision was made to use the percentage of establishments measure. Of the ones based on establishment percentages, the most balanced are the diana/euclidian and hclust/euclidean results (highlighted in red). These were then further studied.

Further tests of methods for calculating distance were done using hclust. These included the standard euclidean distance method as well as the manhattan, maximum and minkowski methods. The euclidean method produces the most balanced set of clusters.

The diana and hclust results were compared with respect to the employment type composition of each cluster. The tables below show the percentage makeup of each cluster by employment type. The clusters are names by the employment type that predominates in the cluster.

Establishment Mixes in Clusters Created by Diana

	AGF	MIN	UTL	CNS	MFG	WHL	RTL	TRN	INF	FIN	REL	PRF	MNG	ADM	EDU	HLH	REC	ACC	RST	OSV	PUB
Finance	2	0	1	4	1	2	2	2	3	42	5	2	2	2	3	12	0	0	6	7	4
Prof	1	0	0	4	2	3	3	1	3	17	7	32	2	2	2	9	1	1	3	3	2
Admin	1	0	0	8	2	3	0	9	2	5	6	10	1	36	2	2	2	0	4	6	3
Health	0	0	0	3	2	1	3	1	2	1	2	4	1	2	3	57	1	0	3	11	1
Restaurant	0	0	0	2	2	0	11	0	3	6	6	0	1	1	1	3	6	5	44	6	1
Retail	0	0	0	2	3	3	45	1	2	6	3	4	1	3	1	1	1	1	14	7	0
Other Srv	0	0	0	3	0	0	5	1	5	0	6	2	0	1	5	0	5	2	22	43	0
Manufac	4	0	0	18	23	20	3	10	2	0	4	1	1	0	1	0	1	0	2	8	0

Establishment Mixes in Clusters Created by Hclust

	AGF	MIN	UTL	CNS	MFG	WHL	RTL	TRN	INF	FIN	REL	PRF	MNG	ADM	EDU	HLH	REC	ACC	RST	OSV	PUB
Health	0	0	0	2	3	0	1	0	2	7	3	12	2	3	1	57	1	0	1	2	1
Finance	1	0	0	4	2	4	2	1	4	39	5	12	4	4	2	9	1	0	1	4	2
Prof	1	0	0	7	1	0	0	1	0	9	11	50	0	7	2	1	0	2	1	5	1
Wholesale	3	0	0	11	4	50	1	3	0	0	7	9	0	5	0	1	0	0	0	5	0
Restaurant	1	0	0	0	2	2	1	2	2	8	4	0	2	2	1	4	4	6	54	6	1
Retail	0	0	0	2	2	2	42	1	2	7	4	5	1	3	1	3	1	1	17	7	1
Other Srv	1	0	0	1	0	7	5	0	6	4	5	3	0	0	5	8	4	1	1	49	1
Manufac	3	0	1	16	20	6	6	10	2	1	4	3	2	9	3	3	2	1	2	6	2

The results show much similarity in the types of clusters identified. Most of the clusters are the same in terms of the employment types that dominate them. Several of these are very similar in the proportions of the establishments of the dominating type (Finance, Health, Retail, Other Srv). The differences in dominating type proportions are greater for the Professional and Restaurant types.

	Diana	Hclust
Finance	42	39
Prof	32	50
Health	57	57
Restaurant	44	54
Retail	45	42
Other Srv	43	49

The Manufacturing category, which doesn't have a dominant type in either case, does have similar mixes of the predominant representatives

	CNS	MFG	WHL	TRN
Diana	18	23	20	10
Hclust	16	20	6	10

The exception here is wholesale (WHL) which makes up a major part of the manufacturing cluster in diana, but a much smaller part in hclust. The reason for this is that hclust identifies a separate cluster dominated by wholesale. Diana's 8th cluster is an administrative cluster. Hcluster spreads administration establishments among various clusters. A wholesale cluster seems to be a more useful and practical cluster than an administration cluster. Wholesaling is a more basic function in the flow of goods in the economy. Administration is a support function.

The hclust results also produce stronger clusters. A cluster is stronger when there is a more pronounced difference in the percentage of types that dominate the cluster and the percentages of the minor business types. A stronger cluster would be shown by a higher variance in the percentages. The following table shows that in more cases, hclust has higher variances. The sum of squared variances for hclust is higher than for Diana. For these reasons, the hclust results were chosen for use in the model.

Estimation and Calibration of the Location Models

The steps for locating developments is described in enough detail above that it is unnecessary to describe them here. The data used in key steps in the process is described however.

The identification of candidate TAZs uses inventories of land available by plan category and TAZ and ratings of compatibility of development types with the plan categories. The model uses five general plan categories: urban residential (Res), urban commercial (Com), urban industrial (Ind), urban open space (Os), and rural (Rur). The urban areas were inventoried by these classifications by the Rogue Valley Council of Governments (RVCOG). The RVCOG also developed an inventory of land that is undevelopable because of flooding, wetland or steep slope constraints. The constrained areas were tabulated by TAZ and these constraints were uniformly allocated to all plan categories in the TAZ. The developable land in each plan category was then inventoried by TAZ.

The initial specification of the RPS work called for the simulation to start after 2030. The model was to use the 2030 allocations of households and employment developed for the regional transportation plan as a given. This required converting the households and employment into an amount of land occupied. This was done for households using the household models to convert households by size, income and age-of-head into building types and then converting into area consumed using the household averages by type used in the model. Similarly, the employment by type was used to calculate the area consumed using the averages per employee by employment type. The consumption of land was proportionally allocated to plan categories in each TAZ.

This approach is being revised for the final LUSDR runs. The technical advisory committee for the RPS project expressed the strong desire for the LUSDR model to be run from the current time into the future. This will require a recalculation of the intial areas.

The compatibilities of development types with plan categories was developed locally through a judgement and consensus process. A score in the range of 0 to 1 was assigned to represent compatibility. 0 means that the development cannot occur in the plan category. 1 means that the development can occur with absolute certainty. These scores are used in Monte Carlo processes to chose whether a particular development can locate in a plan category. Figure 15 shows the scores used in the model.

Figure 15
Plan Compatibility Scores

	Plan Category				
ModelType	Res	Com	Ind	Os	Rur
A5P	1	0.5	0	0	0
SFA	1	0.5	0	0	0
MHpark	1	0.5	0.2	0	0
MHsub	1	0.5	0.1	0	0.01
SFDH	1	0.5	0.1	0	0.01
SFDM	1	0.5	0.1	0	0.01
ACC	0	1	0.25	0	0
ADM	0.25	1	0.25	0	0
AGF	0	0.25	1	0	1
CNS	0	0.5	1	0	0
EDU	0.75	0.25	0	0	0
FIN	0.25	1	0.25	0	0
FIN_CLUST	0.25	1	0.25	0	0
HLH	0.3	1	0.2	0	0
HLH_CLUST	0.3	1	0.2	0	0
INF	0.25	1	0.25	0	0
MFG	0	0.25	1	0	0
MFG_CLUST	0	0.25	1	0	0
MIN	0	0	1	0	1
MNG	0.25	1	0.25	0	0
OSV	0.25	1	0.25	0	0
OSV_CLUST	0.25	1	0.25	0	0
PRF	0.25	1	0.25	0	0
PRF_CLUST	0.25	1	0.25	0	0
PUB	0.75	1	0.5	0	0
REC	0.2	1	0	0.1	0
REL	0	0.75	0.5	0	0
RST	0.1	1	0.25	0	0
RST_CLUST	0.1	1	0.25	0	0
RTL	0.25	1	0.25	0	0
RTL_CLUST	0.25	1	0.25	0	0
TRN	0	0.5	1	0	0
UTL	0	0.5	1	0	0
WHL	0	0.25	1	0	0
WHL_CLUST	0	0.25	1	0	0

Location preferences probabilities are established using a set of binary logistic regression models. These models identify the probability that development of a type is located in a TAZ. As described earlier, the variables in these models are:

- Slope
- Distance to the nearest interchange (IntDist)
- Traffic exposure (Exposure)
- Local employment accessibility (LEA1)
- Regional employment accessibility (LEA0.0625)
- Local household accessibility (LHA1)
- Regional household accessibility (LHA0.0625)

The traffic exposure variable was developed to measure the exposure of TAZs to traffic while avoiding autocorrelation problems. A uniform matrix of 1/10 of a trip was assigned to the network as a peak hour assignment. This measures the relative number of paths using each link subject to enough congestion to cause some divergence from the shortest path. The VMT on links within buffers around TAZs using this assignment was used to produce this measure.

The accessibility measures were computed using a simple exponential decay function. This measure is simple to compute and the same formulation can be used to measure local accessibility and regional accessibility. Only the coefficient needs to be changed. Travel times from the model were used as the impedence term. The log of employment and the log of households were used as the size term. Several coefficients for the decay were used. The best fits were found with a local accessibility coefficient of 1 and a regional accessibility coefficient of 0.0625.

Figure 16 shows the final coefficients for residential developments.

For business developments, the large number of development types would make for an unwieldy and hard to understand set of location models. Therefore business developments were clustered into location groupings. This was done by estimating models for each development type and then performing a cluster analysis on the coefficients of the models. Fairly sensible clusters were developed using this method. Some adjustments were then made to the clusters to group uses that seemed more alike. Figure 17 shows the location groupings, the model coefficients for each grouping and the coefficients for the location groupings.

Application of these models showed that they do not adequately respond to slope. The models showed probabilities that were unreasonably high on steep slopes for a number of uses. This probably occurred because very little development exists on steep slopes and so the estimated models would not be properly sensitive. To address this problem a steep slope variable was created. This variable has the value of slope where slope is greater than or equal to 3 degrees and has the value of 0 where slope is less than 3 degrees. A number of coefficients were tested to produce low probabilities of development on steep slopes. Values were judged to be adequate based on mapping of the probabilities and consideration of whether development of the various types would reasonably be expected to occur on the areas mapped as having higher probabilities.

Resulting probability mappings for the base year are shown in Figures 18 through 31.

Figure 16
Residential Location Model Coefficients

Residential Type		(Intercept)	Slope	IntDist	Exposure	Local Emp (LEA1)	Reg Emp (LEA0.0625)	Local Hh (LHA1)	Reg Hh (LHA0.0625)
Aptmt	Coeff	(4.42036)	(0.00477)	0.19166	(0.00002)	(0.11010)	0.00181	0.20673	0.00010
n=190	Signif	***		**		***	***	***	
Condo	Coeff	(5.20295)	0.04097	(0.11811)	(0.00002)	(0.09786)	0.00095	0.07644	0.00142
n=62	Signif	***				*	*	.	**
MHpark	Coeff	(5.84038)	(0.13077)	0.31449	0.00033	0.02198	(0.00056)	(0.11060)	0.00269
n=63	Signif	***	*	***	***			.	***
MHsub	Coeff	(4.73030)	(0.22833)	0.22260	(0.00004)	(0.04122)	0.00012	(0.05853)	0.00259
n=85	Signif	***	***	**					***
SFsubH	Coeff	(4.08622)	0.16130	0.07782	(0.00007)	(0.06780)	0.00052	0.08015	0.00134
n=193	Signif	***	***			*	.	**	***
SFsubM	Coeff	(1.92533)	(0.04322)	0.02819	(0.00015)	(0.23891)	0.00091	0.32216	0.00162
n=456	Signif	***	.		**	***	***	***	***

Key		
	(0.50)	negative numbers
	***	significant at less than 0.1% level or better
	**	significant at 1% level
	*	significant at 5% level
	.	significant at 10% level

Figure 17
Business Development Location Coefficients

Employment Type		(Intercept)	Slope	IntDist	Exposure	Local Emp (EA1)	Reg Emp (LEA0.0625)	Local Hh (LHA1)	Reg Hh (LHA0.0625)
CNS	Coeff	(2.73063)	0.03822	0.00000	(0.00011)	(0.00154)	0.00105	(0.10135)	0.00178
n=247	Signif	***	.		*	***	***	***	***
MFG	Coeff	(3.28479)	0.00000	0.00000	0.00000	(0.00084)	0.00176	(0.05138)	0.00000
n=79	Signif	***				*	***	.	
EmpGrp1	Coeff	(2.23407)	0.02915	0.01336	(0.00011)	(0.00101)	0.00122	(0.10715)	0.00147
n=286	Signif	***			**	***	***	***	***
Final Coefficients		(1.99200)	0.00000	0.00000	(0.00012)	(0.00097)	0.00115	(0.11576)	0.00149

Employment Type		(Intercept)	Slope	IntDist	Exposure	Local Emp (EA1)	Reg Emp (LEA0.0625)	Local Hh (LHA1)	Reg Hh (LHA0.0625)
WHL	Coeff	(4.18547)	0.00000	0.18830	0.00000	(0.00103)	0.00207	0.00000	0.00000
n=101	Signif	***		**		**	***		
MFG_CLUST	Coeff	(4.14601)	0.00000	0.00000	0.00000	(0.00054)	0.00234	0.00000	(0.00072)
n=98	Signif	***				*	***		**
REL	Coeff	(4.11877)	0.00000	0.00000	0.00000	0.00000	0.00100	0.00000	0.00101
n=100	Signif	***					***		***
EmpGrp2	Coeff	(3.03997)	0.03463	0.08673	0.00003	(0.00046)	0.00183	(0.03069)	0.00030
n=241	Signif	***				**	***	.	
Final Coefficients		(2.31900)	0.00000	0.00000	0.00000	(0.00054)	0.00163	0.00000	0.00000

Employment Type		(Intercept)	Slope	IntDist	Exposure	Local Emp (EA1)	Reg Emp (LEA0.0625)	Local Hh (LHA1)	Reg Hh (LHA0.0625)
AGF	Coeff	(3.88339)	0.00000	0.00000	0.00000	(0.00236)	0.00104	0.00000	0.00062
n=57	Signif	***				*	**		.
MIN	Coeff	(3.87178)	0.00000	0.00000	0.00000	0.00000	0.00310	0.00000	0.00000
n=5	Signif	*					*		
EmpGrp3	Coeff	(3.53561)	0.01001	0.06771	0.00006	(0.00293)	0.00121	(0.05790)	0.00039
n=62	Signif	***				*	***		
Final Coefficients		(3.14100)	0.00000	0.00000	0.00000	(0.00411)	0.00137	0.00000	0.00000

Figure 17 (Continued)
Business Development Location Coefficients

Employment Type		(Intercept)	Slope	IntDist	Exposure	Local Emp (EA1)	Reg Emp (LEA0.0625)	Local Hh (LHA1)	Reg Hh (LHA0.0625)
HLH	Coeff	(4.51066)	0.07079	0.00000	0.00000	0.00000	0.00107	0.04446	0.00108
n=143	Signif	***	*				***	*	***
EDU	Coeff	(4.74152)	0.09358	0.00000	(0.00042)	(0.00099)	0.00182	0.00000	0.00000
n=54	Signif	***	**		**	*	***		
ADM	Coeff	(4.66974)	0.00000	0.00000	0.00000	0.00000	0.00078	(0.04519)	0.00178
n=105	Signif	***					***	*	***
FIN	Coeff	(4.65144)	0.00000	0.00000	0.00000	0.00000	0.00119	0.05021	0.00000
n=67	Signif	***					***	*	
OSV	Coeff	(3.71912)	0.00000	0.12110	0.00000	(0.00052)	0.00130	0.00000	0.00087
n=205	Signif	***		*		**	***		***
PRF	Coeff	(4.00267)	0.07856	0.00000	(0.00011)	0.00000	0.00075	0.00000	0.00105
n=115	Signif	***	**		.		***		***
MNG	Coeff	(5.02805)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
n=4	Signif	*							
EmpGrp4	Coeff	(2.96849)	0.05236	0.08983	(0.00012)	(0.00074)	0.00163	0.03377	0.00126
n=280	Signif	***	*	.	**	***	***	.	***
Final Coefficients		(2.64000)	0.04642	0.00000	(0.00015)	(0.00065)	0.00159	0.00000	0.00146

Employment Type		(Intercept)	Slope	IntDist	Exposure	Local Emp (EA1)	Reg Emp (LEA0.0625)	Local Hh (LHA1)	Reg Hh (LHA0.0625)
WHL_CLUST	Coeff	(5.40819)	0.00000	0.00000	0.00000	0.00000	0.00213	0.00000	0.00000
n=21	Signif	***					**		
PUB	Coeff	(5.52316)	0.00000	0.33222	0.00000	0.00000	0.00117	0.07340	0.00000
n=27	Signif	***		*			*	*	
TRN	Coeff	(5.36152)	(0.07998)	0.38680	0.00000	0.00000	0.00185	(0.09826)	0.00083
n=58	Signif	***	.	***			***	**	**
EmpGrp5	Coeff	(4.73838)	(0.10365)	0.38226	0.00000	(0.00022)	0.00175	(0.01589)	0.00034
n=100	Signif	***	*	***			***		
Final Coefficients		(4.19700)	(0.09751)	0.36020	0.00000	0.00000	0.00149	0.00000	0.00000

Employment Type		(Intercept)	Slope	IntDist	Exposure	Local Emp (EA1)	Reg Emp (LEA0.0625)	Local Hh (LHA1)	Reg Hh (LHA0.0625)
RTL_CLUST	Coeff	(6.27008)	0.09495	0.00000	0.00016	(0.00037)	0.00282	0.06552	(0.00066)
n=94	Signif	***	*		**	.	***	**	*
ACC	Coeff	(5.79317)	0.18639	0.00000	0.00028	0.00000	0.00096	0.15894	(0.00096)
n=31	Signif	***	***		***		*	***	*
OSV_CLUST	Coeff	(5.77925)	0.00000	0.00000	0.00000	0.00000	0.00171	0.00000	0.00000
n=37	Signif	***					***		
RTL	Coeff	(3.90807)	0.00000	0.00000	0.00012	(0.00080)	0.00200	0.04452	0.00000
n=165	Signif	***			**	***	***	*	
RST	Coeff	(4.92089)	0.00000	0.15061	0.00008	(0.00064)	0.00176	0.06577	0.00000
n=91	Signif	***		.	.	**	***	**	
REC	Coeff	(5.06571)	0.00000	0.00000	0.00000	0.00000	0.00134	0.00000	0.00000
n=32	Signif	***					***		
EmpGrp6	Coeff	(3.30087)	0.05387	0.06901	0.00014	(0.00059)	0.00214	0.05474	(0.00036)
n=161	Signif	***	*		**	**	***	**	.
Final Coefficients		(3.28000)	0.05332	0.00000	0.00012	(0.00048)	0.00206	0.03104	0.00000

Figure 17 (Continued)
Business Development Location Coefficients

Employment Type		(Intercept)	Slope	IntDist	Exposure	Local Emp (EA1)	Reg Emp (LEA0.0625)	Local Hh (LHA1)	Reg Hh (LHA0.0625)
HLH_CLUST	Coeff	(8.04339)	0.00000	0.00000	(0.00029)	0.00000	0.00228	0.00000	0.00162
n=31	Signif	***			*		***		***
EmpGrp7	Coeff	(8.04339)	0.02437	0.01111	(0.00029)	0.00029	0.00228	(0.04081)	0.00162
n=31	Signif	***			*		***		***
Final Coefficients		(8.17500)	0.00000	0.00000	(0.00022)	0.00000	0.00246	0.00000	0.00128

Employment Type		(Intercept)	Slope	IntDist	Exposure	Local Emp (EA1)	Reg Emp (LEA0.0625)	Local Hh (LHA1)	Reg Hh (LHA0.0625)
FIN_CLUST	Coeff	(7.09593)	0.00000	0.00000	0.00000	0.00000	0.00168	0.08386	0.00000
n=25	Signif	***					**	*	
UTL	Coeff	(6.55954)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00149
n=9	Signif	***							*
PRF_CLUST	Coeff	(6.80425)	0.15954	0.00000	0.00000	0.00000	0.00192	0.12433	0.00000
n=21	Signif	***	*				**	**	
RST_CLUST	Coeff	(6.73505)	0.00000	0.00000	0.00000	0.00000	0.00208	0.06746	0.00000
n=35	Signif	***					***	*	
INF	Coeff	(6.21834)	0.08505	0.00000	0.00000	0.00000	0.00191	0.00000	0.00000
n=38	Signif	***	.				***		
EmpGrp8	Coeff	(5.35235)	0.08816	0.13315	(0.00002)	(0.00025)	0.00203	0.06833	(0.00003)
n=82	Signif	***	*				***	**	
Final Coefficients		(4.73800)	0.08847	0.00000	0.00000	0.00000	0.00169	0.06029	0.00000

Figure 18
Base Year Apartment Location Probabilities

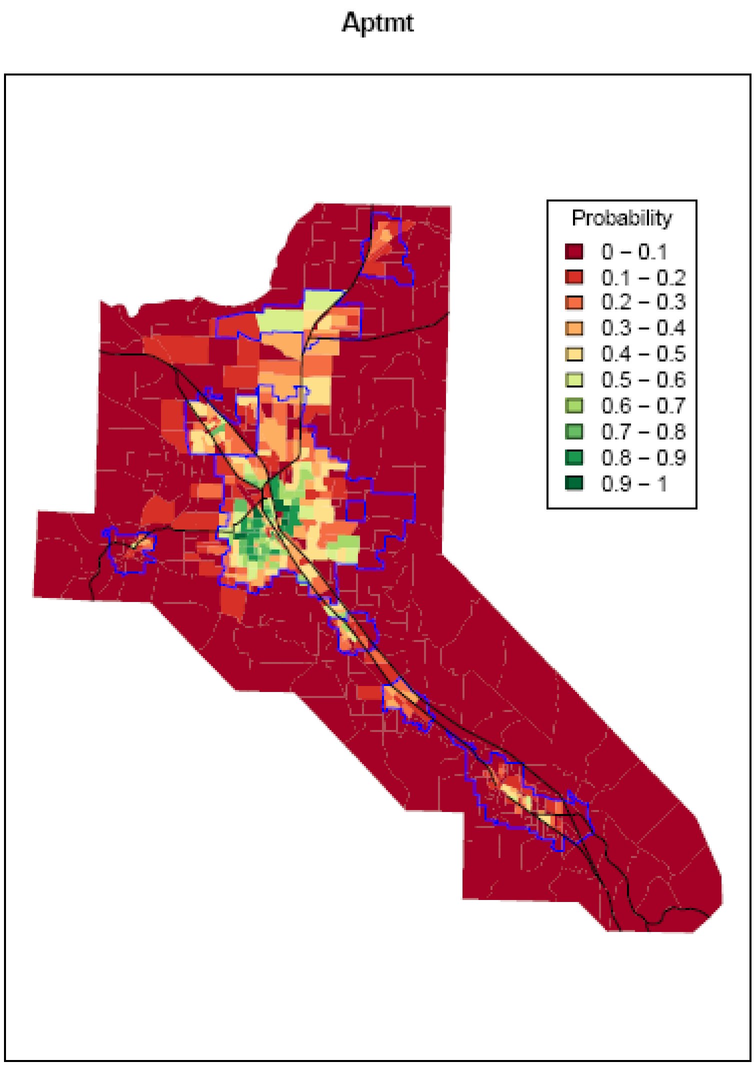


Figure 19
Base Year Condominium Location Probabilities

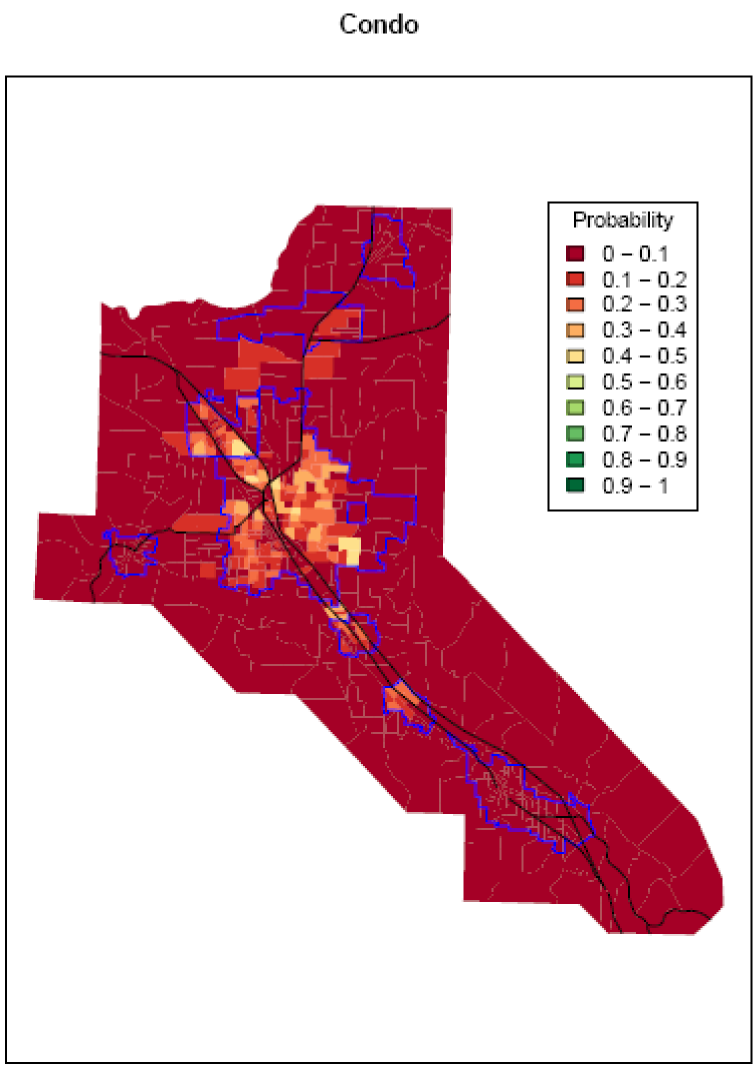


Figure 20
Base Year Mobile Home Park Location Probabilities

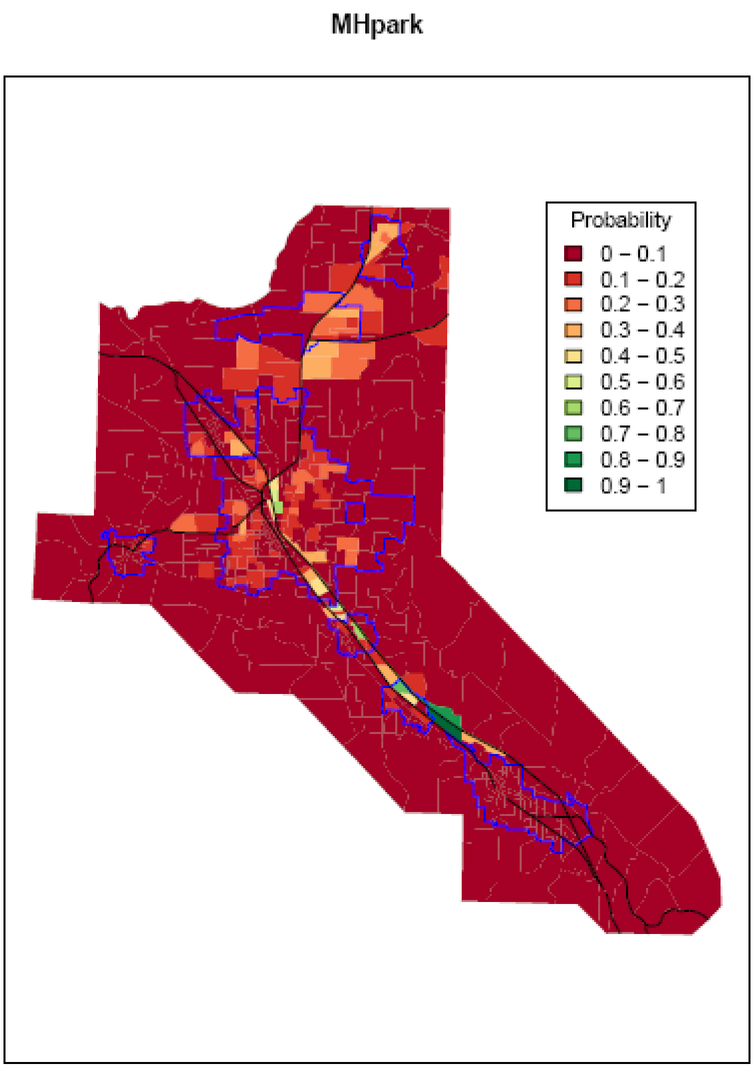


Figure 21
Base Year Mobile Home Subdivision Location Probabilities

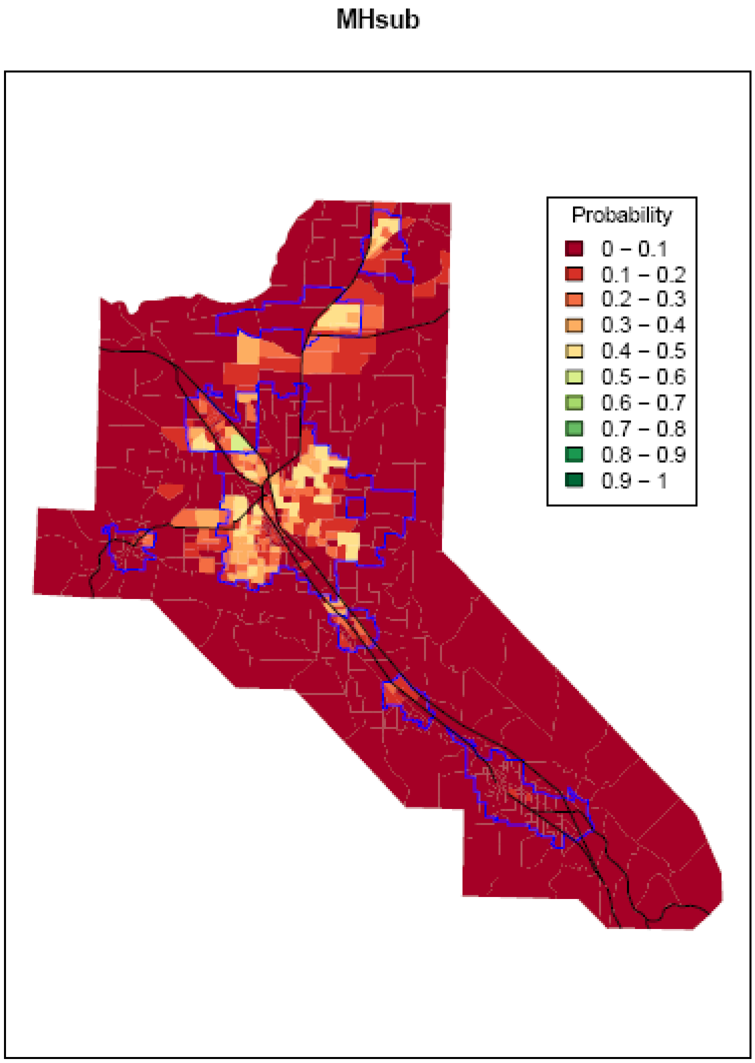


Figure 22
Base Year High Income Single Family Location Probabilities

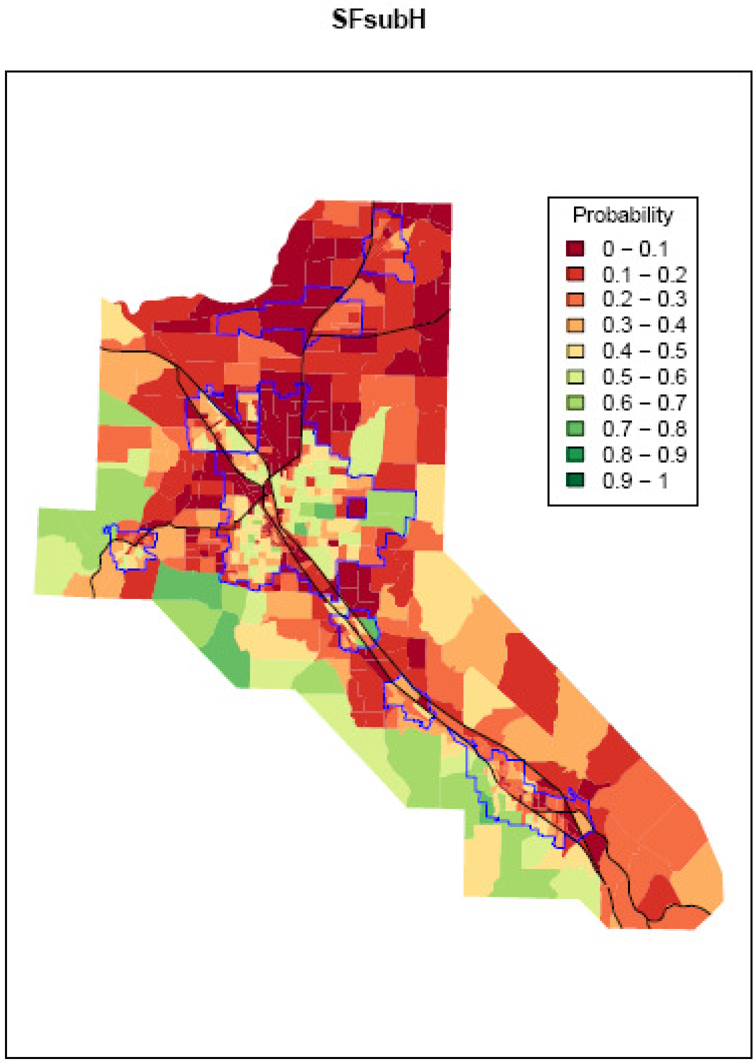


Figure 23
Base Year Moderate Income Single Family Location Probabilities

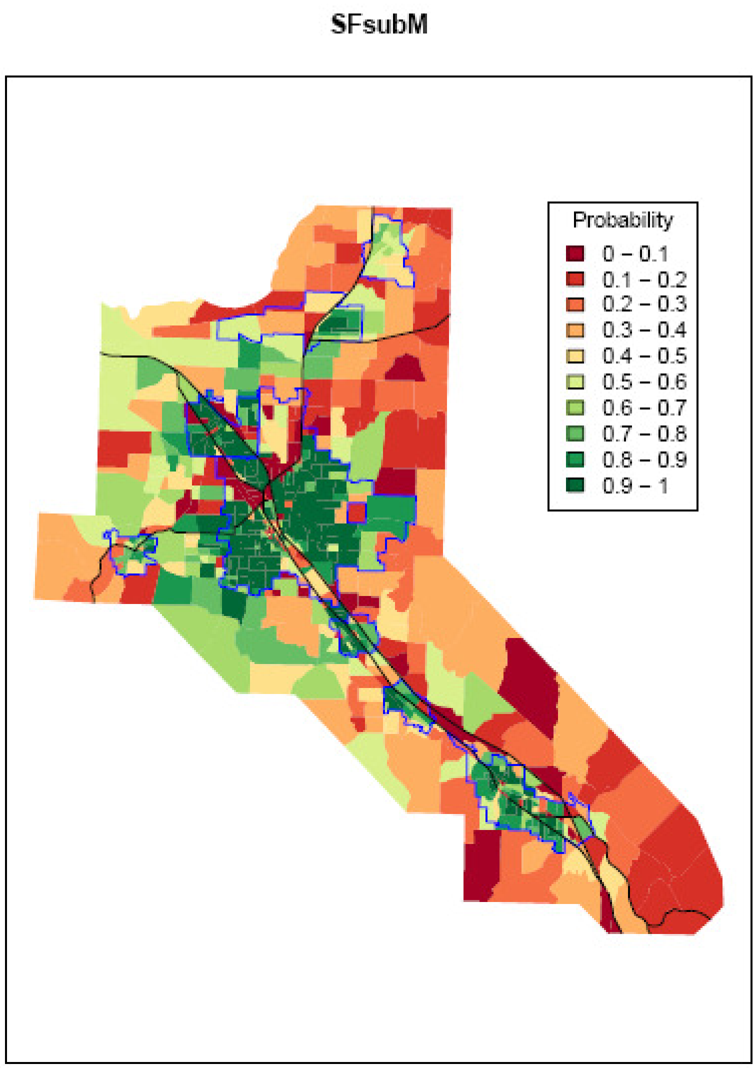


Figure 24
Base Year Employment Group 1 Location Probabilities
(CNS, MFG)

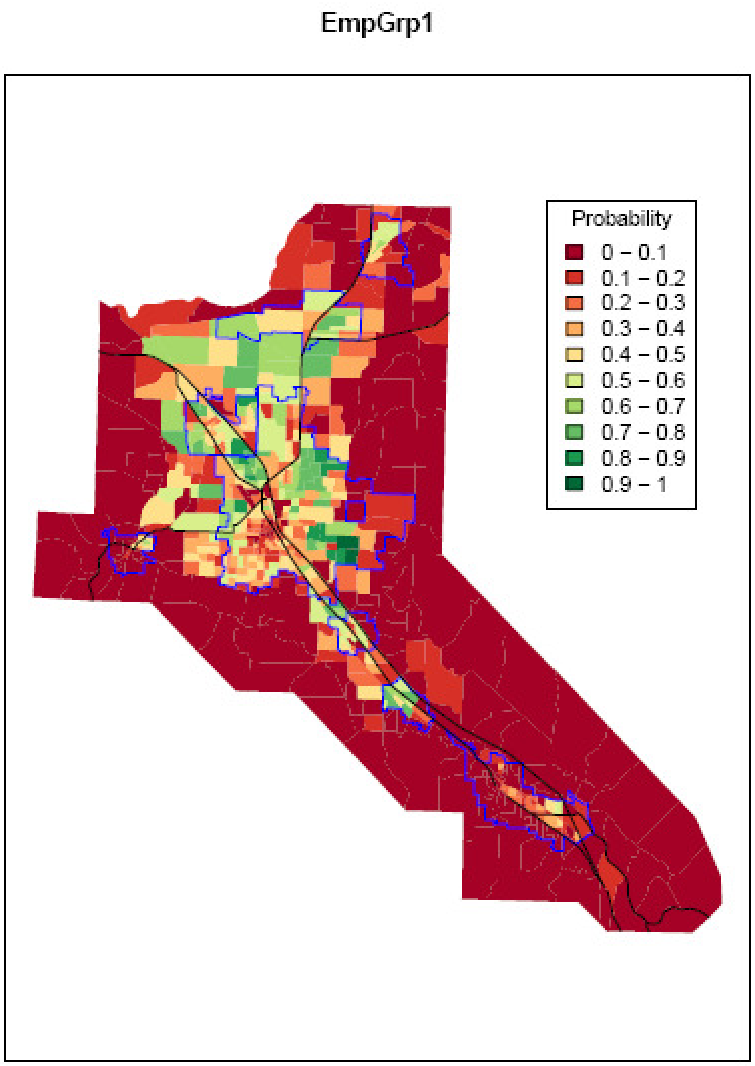


Figure 25
Base Year Employment Group 2 Location Probabilities
(WHL, MFG_CLUST, REL)

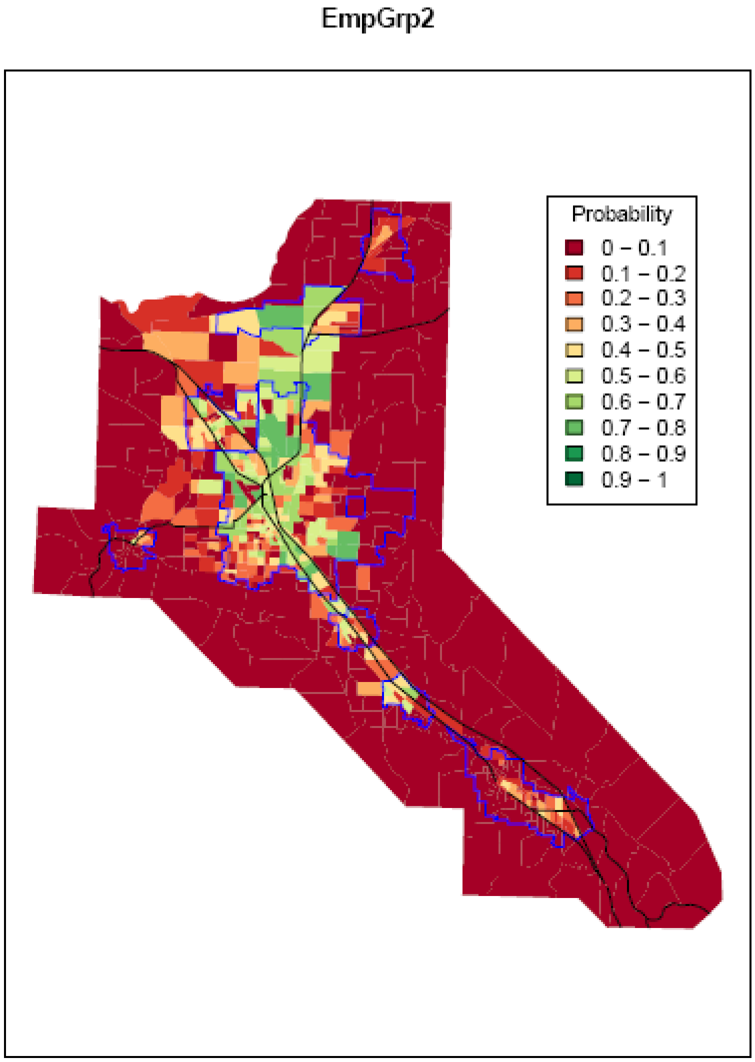


Figure 26
Base Year Employment Group 3 Location Probabilities
(AGF, MIN)

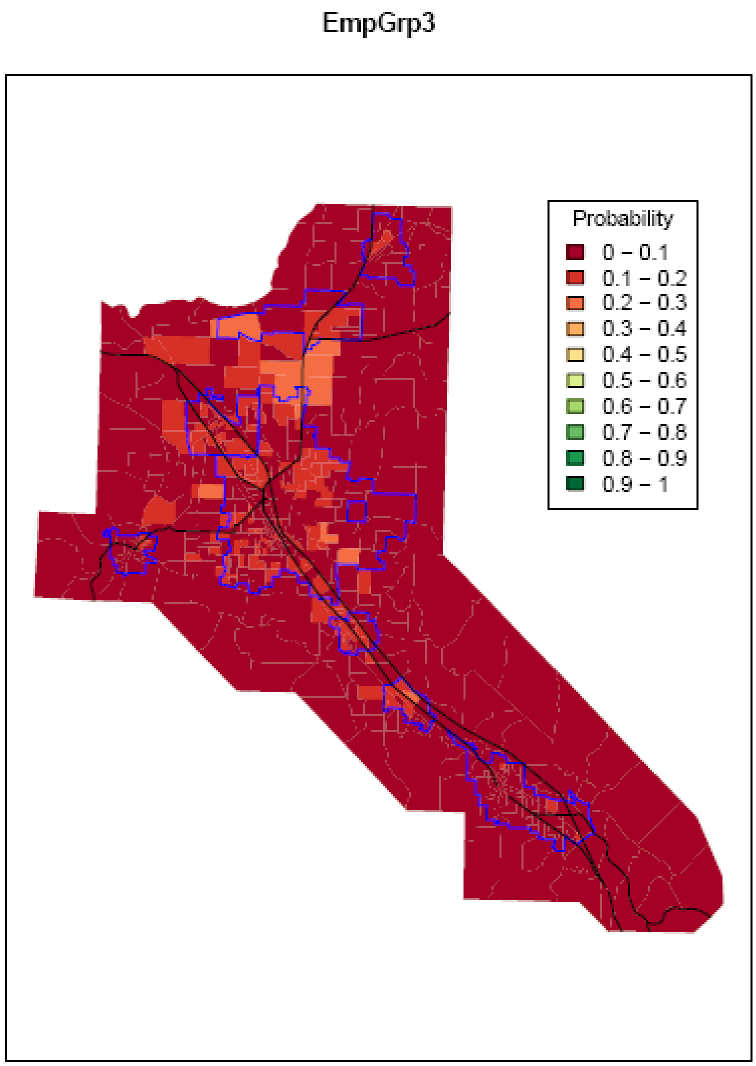


Figure 27
Base Year Employment Group 4 Location Probabilities
(HLH, EDU, ADM, FIN, OSV, PRF, MNG)

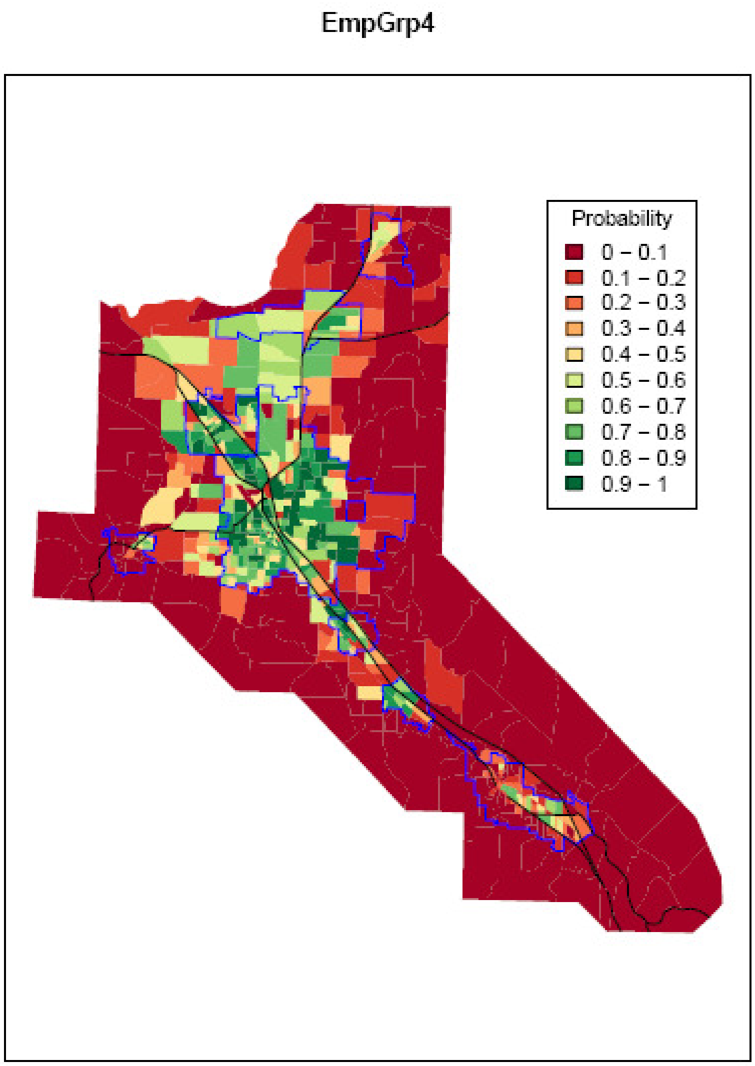


Figure 28
Base Year Employment Group 5 Location Probabilities
(WHL_CLUST, PUB, TRN)

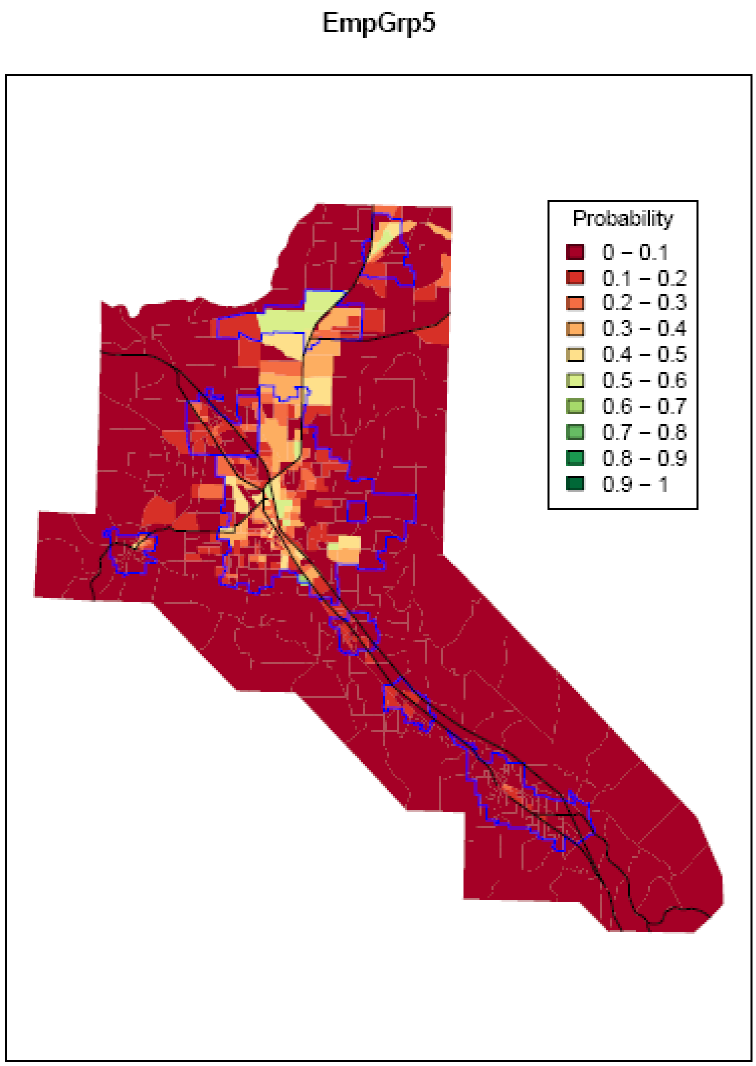


Figure 29
Base Year Employment Group 6 Location Probabilities
(RTL_CLUST, ACC, OSV_CLUST, RTL, RST, REC)

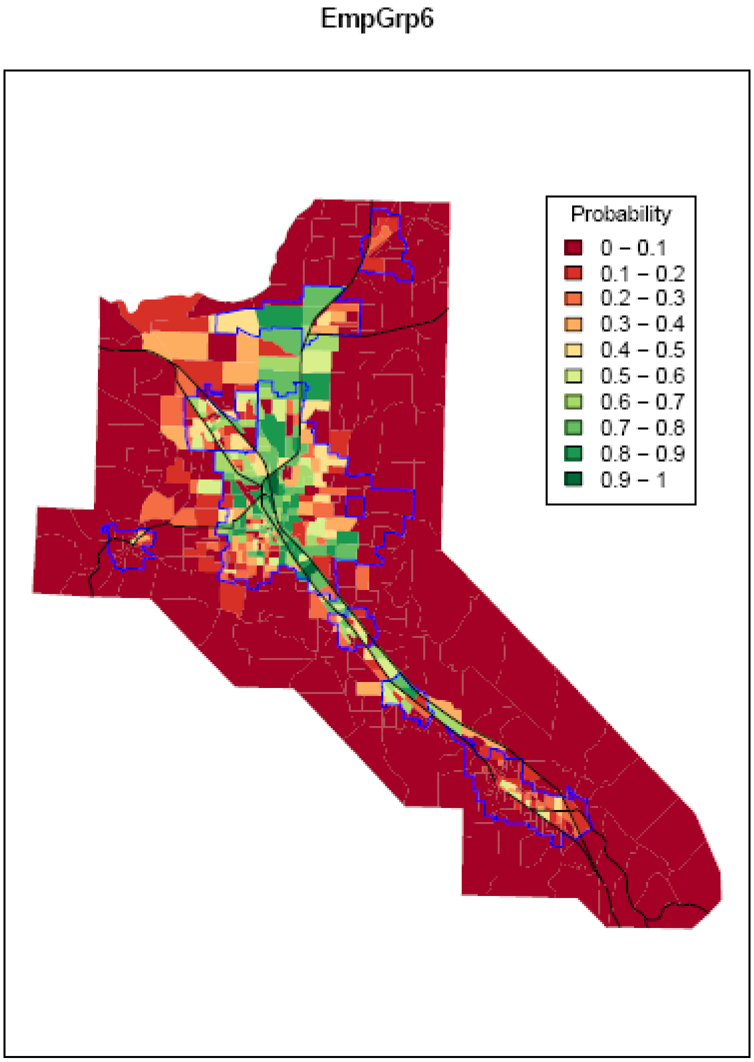


Figure 30
Base Year Employment Group 7 Location Probabilities
(HLH_CLUST)

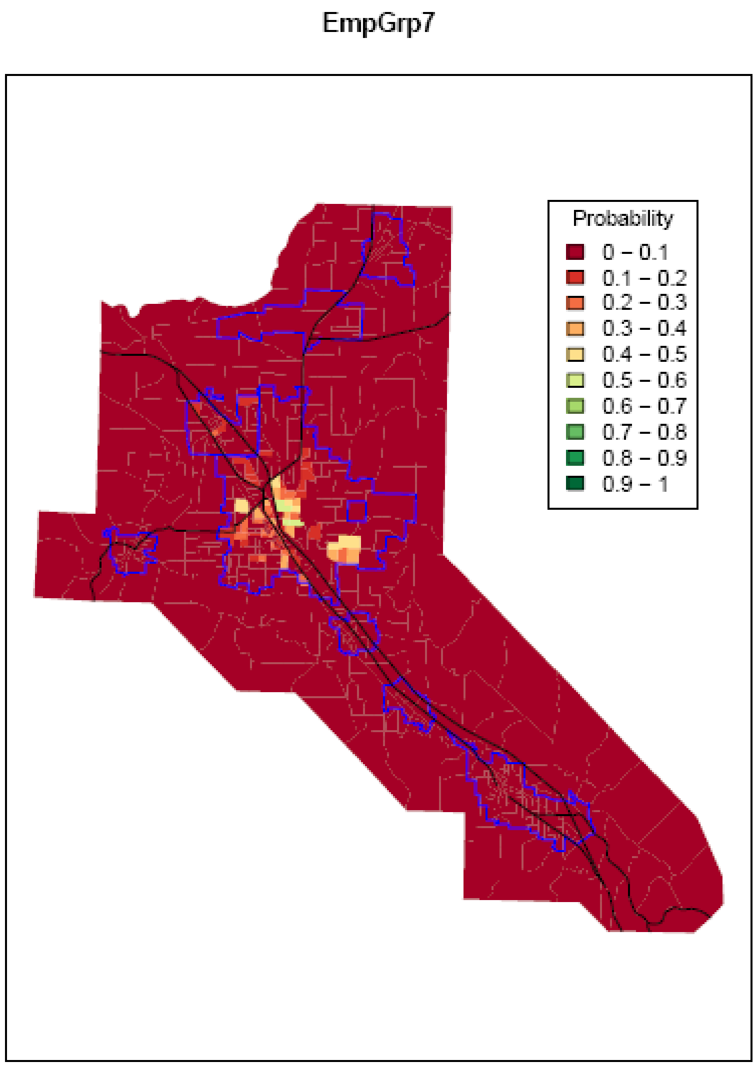
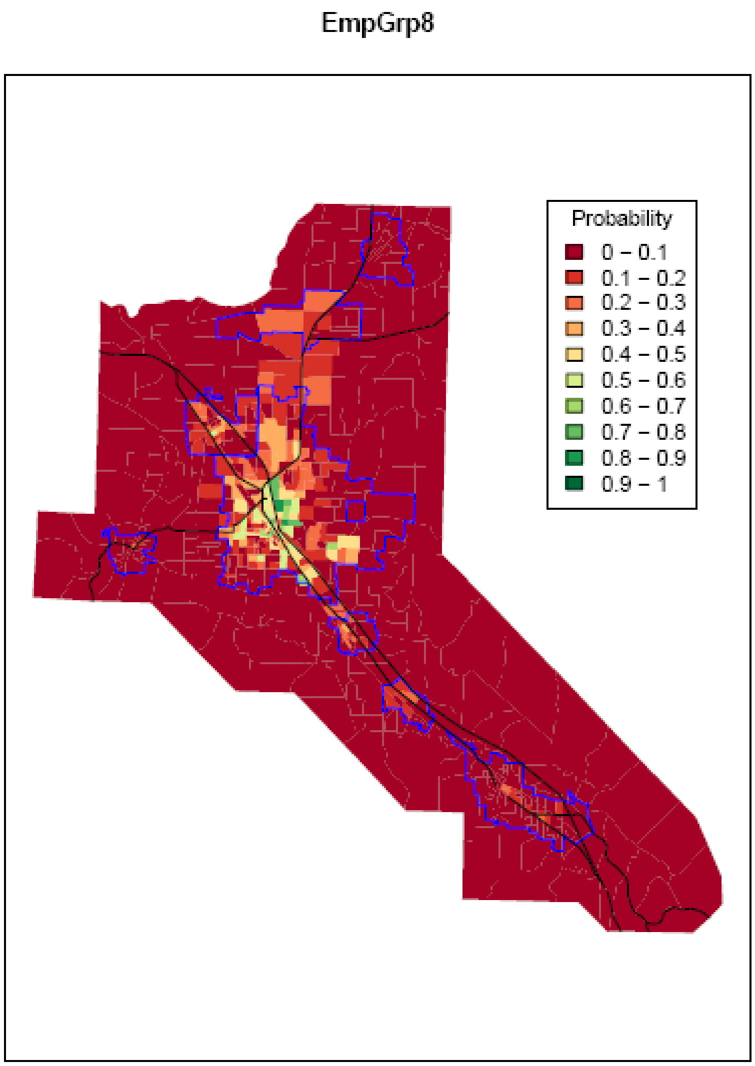


Figure 31
Base Year Employment Group 8 Location Probabilities
(FIN_CLUST, UTL, PRF_CLUST, RST_CLUST, INF)



Whether or not a development can successfully locate in a TAZ is a function of the price that the development is willing to pay compared to the price of competing developments. LUSDR has a simple price model. Tax data was used to calculate the median land values per square foot by cluster type. These values are used as the prices in the model.

It was thought that land values should vary with the degree of preference a development has for a site. A development would be willing to pay more for a more highly preferred site. However, no such relationship was found as shown in Figures 32 through 37.

Figure 32
Plots of Land Values vs. Location Preferences for Various Development Types

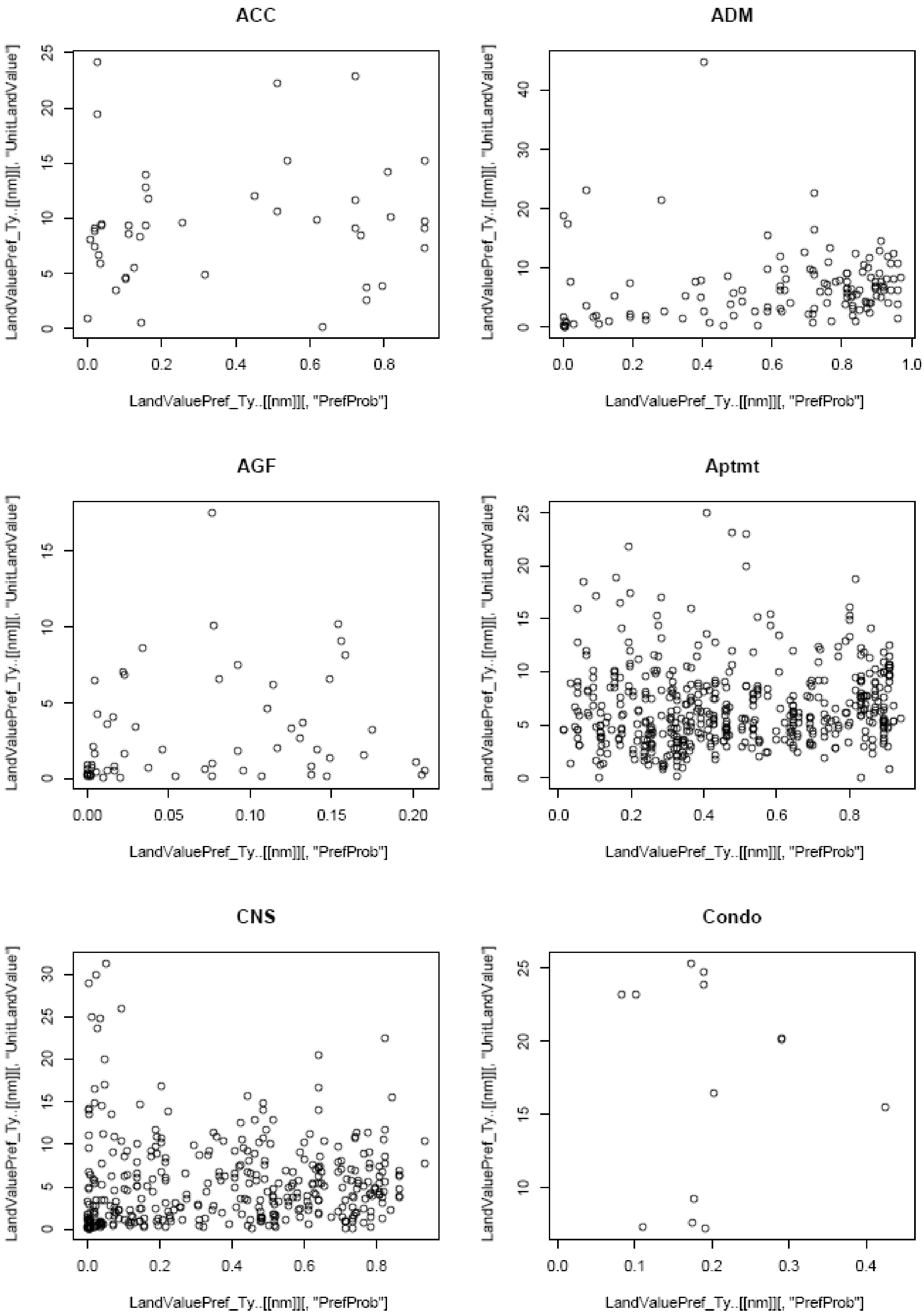


Figure 33
Plots of Land Values vs. Location Preferences for Various Development Types

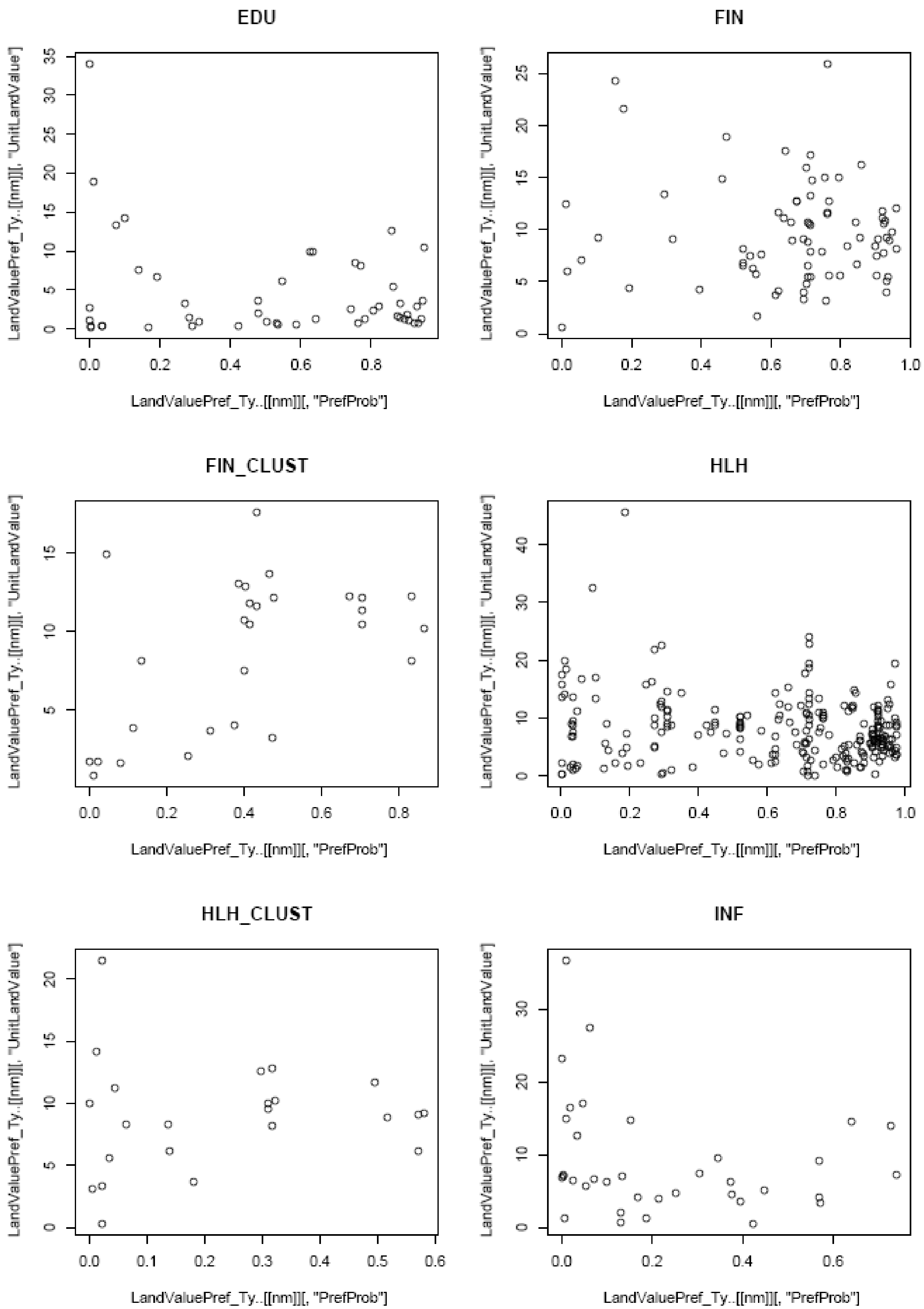


Figure 34
Plots of Land Values vs. Location Preferences for Various Development Types

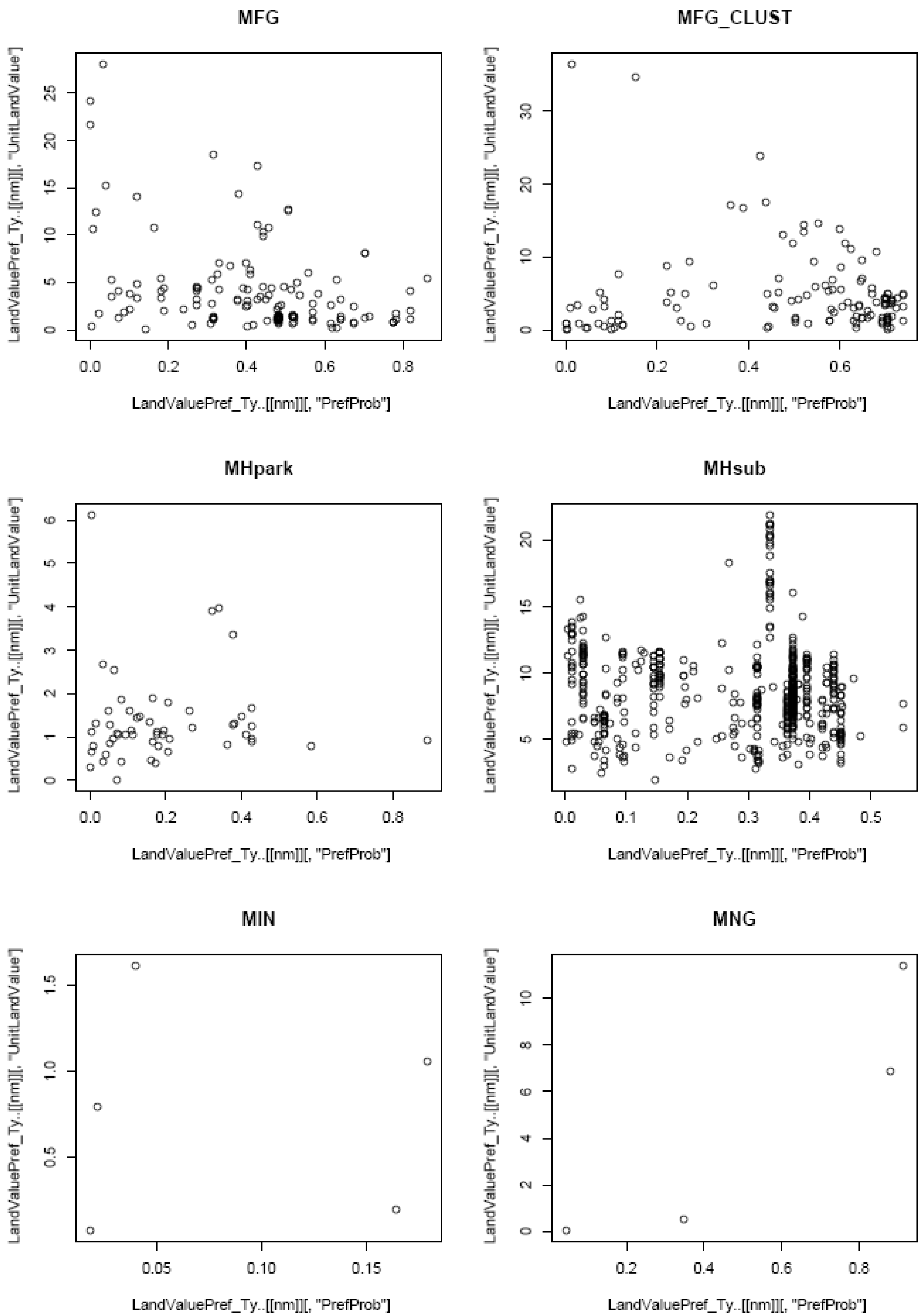


Figure 35
Plots of Land Values vs. Location Preferences for Various Development Types

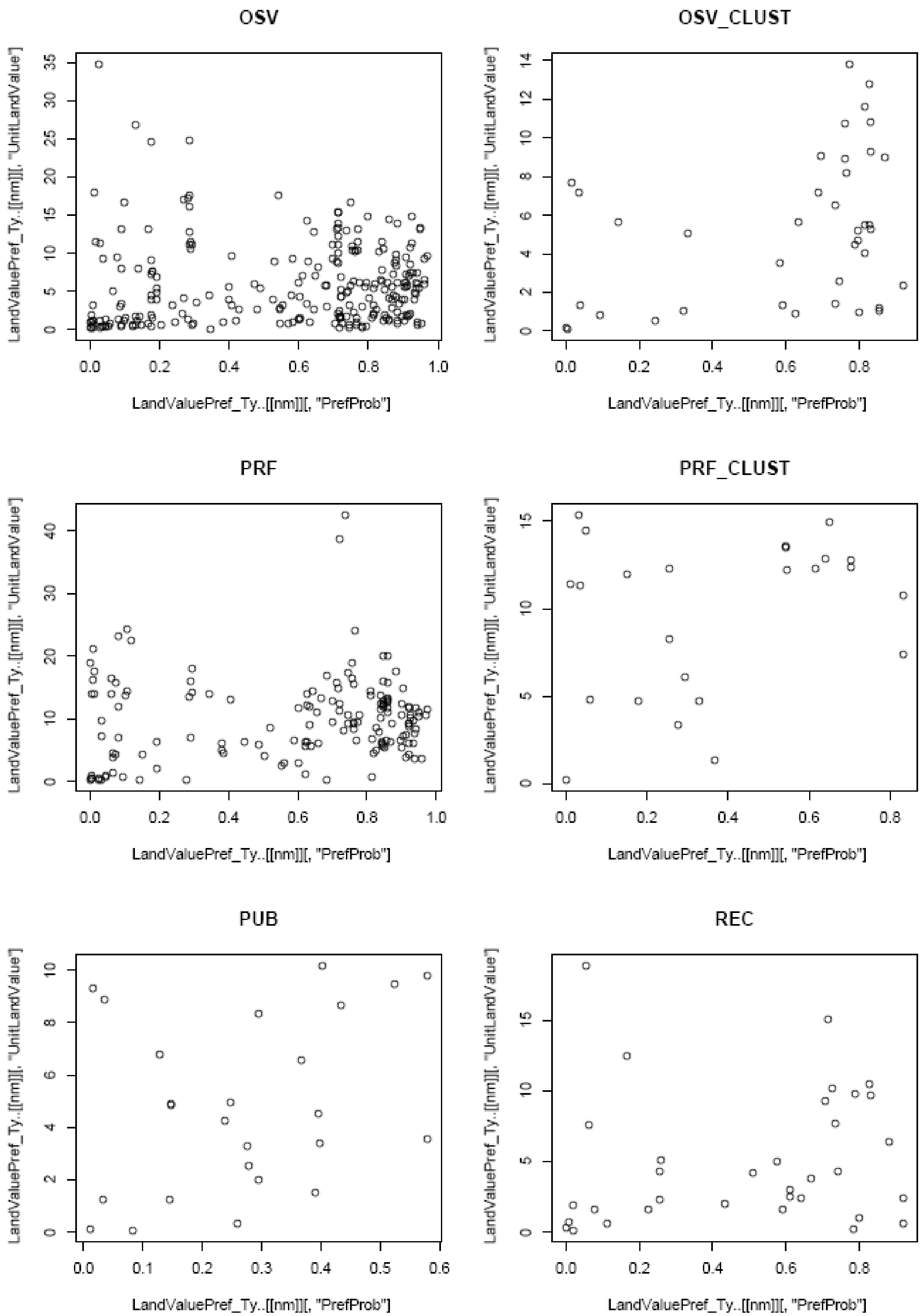


Figure 36
Plots of Land Values vs. Location Preferences for Various Development Types

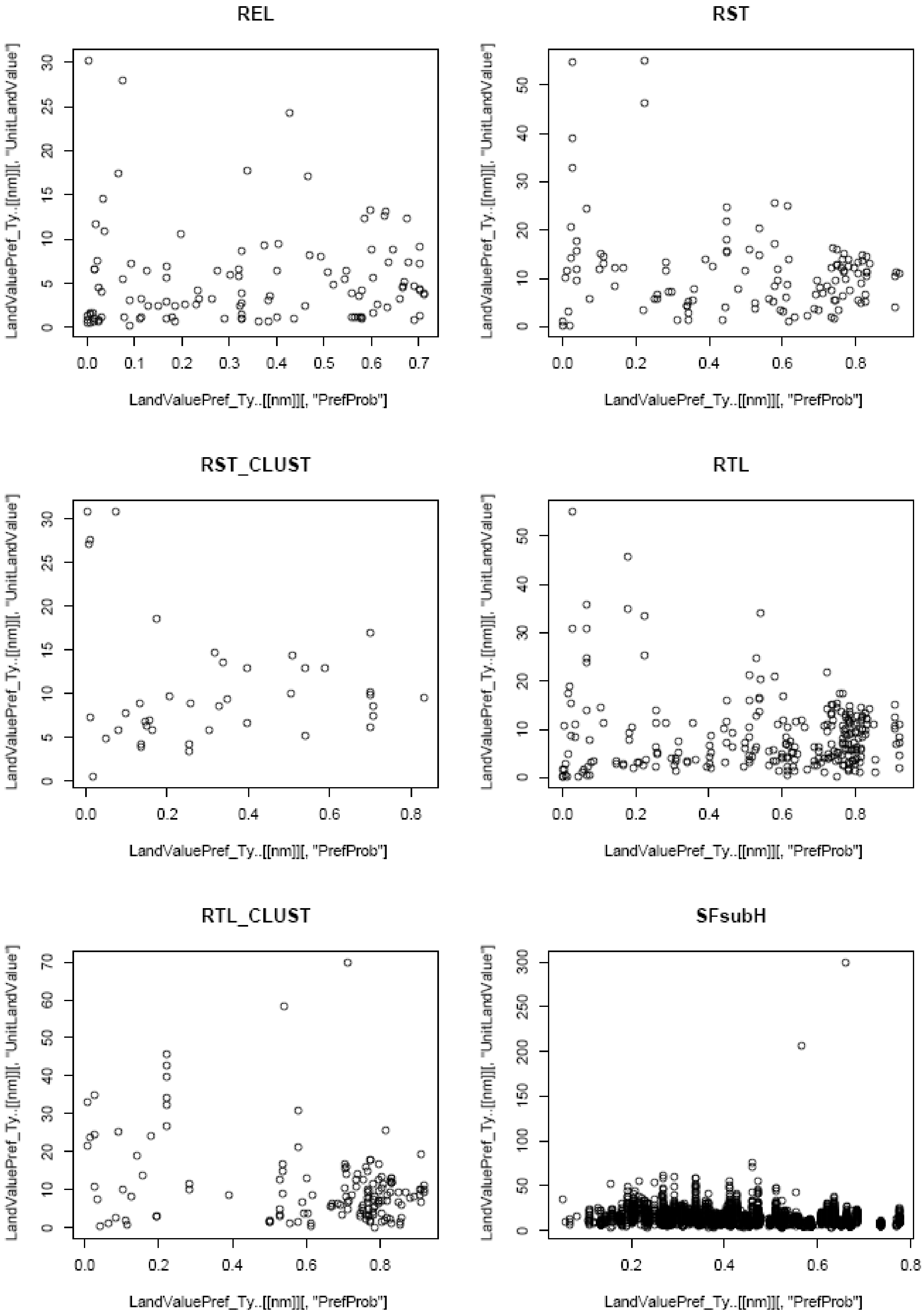
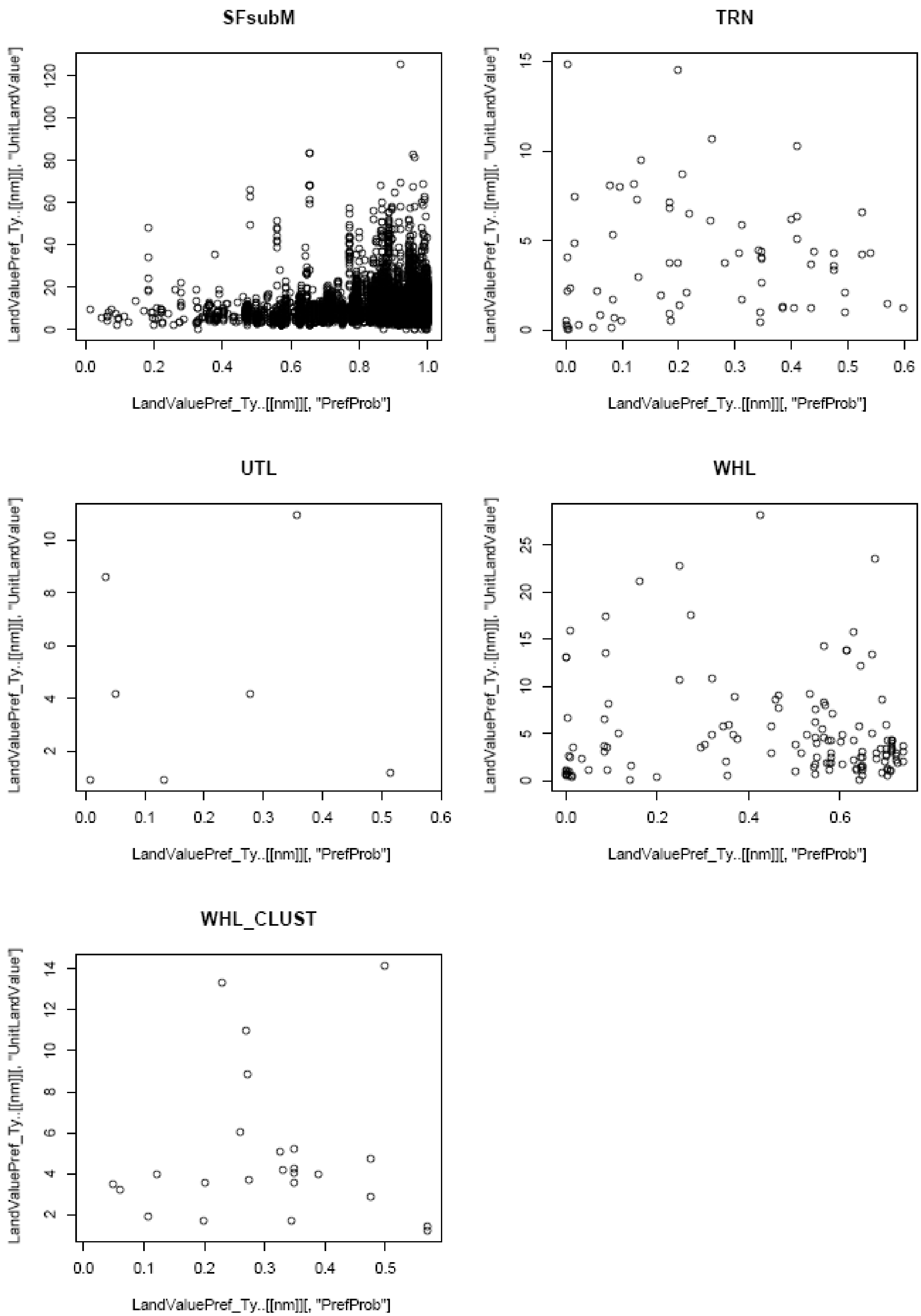


Figure 37
Plots of Land Values vs. Location Preferences for Various Development Types



Application Results

The LUSDR model was run through 40 iterations. The results of these runs are shown in a set of animations contained in a PowerPoint presentation transmitted previously to the Peer Review Panel. The animations show that the model is producing reasonable development patterns and reasonable variations in the patterns reflecting the stochastic influences.