Prepared for

USEPA, Office of Sustainable Communities

DATASET FOR BROWNFIELD AIR AND WATER QUALITY IMPACT EVALUATION

IMPERVIOUS SURFACE GROWTH MODEL

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LIST OF ACRONYMS AND ABBREVIATIONS

AC	Acre
CBG	Census Block Group
DU	Dwelling unit
EMP	Employee
HRLC	High Resolution Land Cover
HU	Housing unit
IC	Impervious Cover
IMP	Impervious
ISC	Impervious Surface Cover
ISG	Impervious Surface Growth
ISGM	Impervious Surface Growth Model
LEHD	Local Employer-Household Dynamics dataset
MPO	Municipal Planning Organization
MSA	Metropolitan/Micropolitan Statistical Area
NLCD	National Land Cover Database
SLI	Smart Location Index (Theobald, et al., 2011)
SPLOM	Scatter Plot Matrix
USEPA	United States Environmental Protection Agency

1. INTRODUCTION

1.1 Background

The redevelopment of Brownfield sites is central to USEPA's mission of protecting human health and the environment. Such redevelopment can directly improve the environment by cleaning up (or capping/isolating) contaminated soils and groundwater. Indirectly, Brownfield redevelopment can also reduce both air emissions and stormwater runoff by accommodating more homes and commercial buildings on previously developed land, which are often located near urban centers thereby also reducing commuting distances.

However, quantifying the water quality impacts of Brownfield redevelopment requires measures of both individual site characteristics and their regional context. The first step in evaluating the potential water quality benefits of Brownfield re-use is to develop summary measures characterizing how particular sites perform in terms of stormwater runoff (impervious surface per square feet of residential / commercial space). In turn, site specific measures must be compared to the average rates for locations in the region where "development would have otherwise gone" to benchmark "environmental performance".[1]

Urban land use forecasting models have been capable of such assessments for some time. However, there is a significant need at the community level for indicators that provide relatively accurate estimations of such outcomes without the need to run a complex and costly forecasting model. This project seeks to develop neighborhood scale measures relative to water quality impacts associated with increasing impervious cover that consider a regional context.

1.2 Model Requirements

Estimating how much impervious surface will be produced by residential and commercial development in specific locations is a challenging task. Some estimation tools are available that take user inputs and provide basic estimates of how much paved land cover will result.[2] However, most tools rely upon rates that are not location specific or require significant user inputs to develop estimates. What is needed for simple comparison studies are simple factors that allow a user to estimate the amount of impervious surface added for every additional increment of residential and commercial development in specific neighborhoods. The intended users of this information are planners and policy makers involved in planning-level analyses of the relative water quality impacts of various regional land use or development scenarios.

[1] Comparing Methodologies to Assess Transportation and Air Quality Impacts of Brownfields and Infill Development. EPA 231-R-01-001. 2001

[2] Impervious Surface Analysis Tool (ISAT) NOAA URL: http://www.csc.noaa.gov/digitalcoast/tools/isat/

This project has resulted in a model that quantifies key location attributes that influence rates of impervious surface produced by new development. The data behind the dependent variable in the model – impervious surface - has been based on nationwide remote sensing of impervious surfaces conducted as part of the National Land Cover Database (Fry et al., 2011) allowing representative sampling of all major urban place types. The statistical model is built upon the attributes of each place, including characteristics of existing development and destination accessibility that influence the intensity and characteristics of development.

The resulting impervious surface growth rate can then be applied to the existing characteristics of census block groups (CBGs) across the country to provide a simple, but place specific method for estimating the amount of additional impervious surface produced by additional development. In turn, the average rates can be used to examine the differences in the amount of imperviousness produced by redevelopment of Brownfield or infill sites relative to alternative "business as usual" development locations in a region.

1.3 Report Organization

This report is organized into the following sections:

Section 1 describes the project background and introduces the requirements of the Impervious Surface Growth Model (ISGM).

Section 2 describes the data sources that were evaluated for use, discusses options that were evaluated for model development, provides observations of data reliability for this effort, and provides model selection recommendations.

Section 3 describes the ISGM that was developed, discusses validation efforts, and describes the ISGM User Interface.

2. DATA SOURCES AND MODEL SELECTION

The ISGM is based on an empirical regression model; therefore model selection was based primarily on the datasets that are available to support the regression analysis effort and their reliability for this application. This section summarizes the data sources that were evaluated for use, discusses key decision points in model selection and development, provides observations of reliability of available datasets for this effort, and describes the recommended model type.

2.1 Data Sources

A variety of potentially applicable datasets were evaluated for their role in supporting the development, application, and/or validation of the ISGM, including:

- Impervious cover datasets
- High resolution aerial photography
- Land cover and land cover change datasets
- Census Block Groups and Census datasets
- Various nationwide boundary datasets (e.g., state and county boundaries)
- Smart Location Index (SLI) (Theobald, et al., 2011)
- Local Employer-Household Dynamics (LEHD) dataset
- Housing unit count estimates, US Census Bureau
- NRDC "Getting Back on Track" assessment of strength of state growth management policies (Bhatt, et al., 2010)
- Protected areas datasets, including the Protected Areas Dataset – US (PADUS V1.2) and NAVTEQ parks and recreation features

The datasets that were considered are introduced in Appendix A.

2.2 Options for Model Form and Development

The ISGM requires a regression model capable of making predictions about impervious surface quantities based on information about a CBG. The form of the model used for the ISGM was selected from a relatively wide range of potential models. Three key decision factors were considered:

- **Is a functional or logical regression more appropriate for use in the ISGM?** Functional models are based on a mathematical function that is "best fit" to observed data. In contrast, logical regression models typically use a "decision tree" type of approach to return an estimate based on distinct combinations of input variables.
- **Is it more reliable to base the ISGM on change estimates or static estimates?** The datasets evaluated potentially allow estimates of changes in impervious surface for each CBG over a fixed window of time, coupled with estimates of change in housing units and employees. Alternatively, the regression could be based on estimated conditions at one snapshot in time and perform mathematical manipulations to yield estimates of net impervious surface growth (ISG) based on differences between CBGs that are at various stages of development intensification.
- **What scale and resolution of remote sensing analysis best balances data quality and data quantity to yield the most reliable model?** Options considered for model development range from focused, high-resolution analysis of a relatively small number of samples (100 to 200) to a much broader analysis at lower data resolution, considering the majority of CBGs (approximately 200,000).

The preliminary data analysis discussed in Section 2.3 was conducted to provide feedback and support for addressing these questions.

2.3 Preliminary Data Analysis

To support evaluation of the key decision points introduced in Section 2.2, a preliminary analysis dataset was developed and analyzed. The quality and reasonableness of this dataset were evaluated, and a preliminary non-parametric regression analysis was performed on various potential model variables. The intents of these analyses were to identify potential uses and limitations of the dataset and quantify the strengths of potential correlations between key independent variables and impervious surface growth metrics to provide feedback relative to the form of statistical model most appropriate for this application.

2.3.1 Preliminary Analysis Dataset

The preliminary analysis dataset included data looked up from existing sources and developed through spatial analysis of nationwide datasets. Estimates were developed for all CBGs that were supported by the extent of the available datasets. The fields in this dataset are described in Table 1. Note that in some cases, the parameters used in the preliminary analysis were refined or improved prior to use in the final regression analysis.

Table 1. Description of Fields in Preliminary Analysis Dataset

Description	Data Source
2001 CBG impervious cover	Spatial analysis of CBG dataset (Theobald et al., 2011) and NLCD 2001/2006 raster datasets (Fry et al., 2011)
2006 CBG impervious cover	Spatial analysis of CBG dataset and NLCD 2001/2006 raster datasets (Fry et al., 2011)
Change in impervious cover (2001-2006)	Calculated
Percent change in impervious cover (2001-2006)	Calculated
2000 occupied housing units	US Census Bureau dataset, provided by USEPA
2006 occupied housing units	US Census Bureau dataset, provided by USEPA
Change in occupied housing units (2001-2006, est)	Linear interpolation
Percent change in occupied housing units (2001-2006, est.)	Calculated
Change in impervious cover per change in occupied housing unit (2001-2006, est.)	Calculated
2002 total jobs	LEHD, downloaded and summarized to CBG
2006 total jobs	LEHD, downloaded and summarized to CBG
Change in total jobs (2001-2006, est.)	Linear extrapolation
Percent change in total jobs (2001-2006, est.)	Calculated
Change in impervious cover per change in total jobs (2001-2006, est.)	Calculated

Description	Data Source
2001-2006 land cover change quantities, grouped into bins based on conversion type such as "Agriculture to Developed Medium Intensity"	Spatial analysis of CBG dataset and NLCD 2006 raster datasets (Fry et al., 2011)
Strength of Urban Growth Boundary; qualitative ranking	"Getting Back on Track" (Bhatt et al., 2010)
High resolution impervious cover estimates for selected CBGs in the Portland, OR metro area (2007), 1 m resolution	Portland Metro, High Resolution Land Cover (2007)
High resolution impervious cover estimates for selected CBGs in the Boston, MA, metro area (2005); 0.5 m resolution	MassGIS (2005)
Aerial photography of selected CBGs in the Portland, OR, metro area (2001 and 2006)	Google Earth Pro "Time Slider"
CBG Geopolitical Attributes, including: • CBG ID • State Name • MSA • Metropolitan Planning Organization (MPO) • Acreage • Private Acreage	Smart Location Index Dataset (Theobald et al., 2011)
Smart Location Index Metrics, including: • CBG total average development density (housing units, population, employment) [3] • CBG private area average development density (housing units, population, employment)[3] • Land use diversity metrics • Urban design metrics • Transit proximity metrics • Destination accessibility metrics • Composite Transportation Location Efficiency Index (TLEI, superseded by SLI) • Composite Smart Location Index (SLI) • Various metrics normalized to US averages	Smart Location Index Dataset (Theobald et al., 2011)

2.3.2 Evaluation of Data Quality and Reasonableness

The preliminary analysis dataset was evaluated for data quality and reasonableness to support decisions about model development and to understand the appropriate uses of these data. Evaluation methods included:

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[3] Average development density and average private area development density reported by the Smart Location Index Dataset were used for preliminary analysis efforts. For the final analysis and regression, these estimates were updated using 2006 housing units and employees counts (See Table 2) and a refined analysis of unprotected areas (see Appendix A).

- Overall trend analyses, summations, and outlier analyses
- Spot checks on derived data against raw data sources
- Reasonableness checks on land cover change dataset, impervious change dataset, housing unit change estimates, and employment change estimates by visual inspection of historic aerial photographs.

The following key observations were made from this analysis:

- Potential independent and dependent variables appear to follow relatively continuous distributions, and relationships are expected to be monotonic.
- The NCLD 2006 dataset (nationwide) appears to be reliable at estimating average imperviousness at the CBG scale based on comparisons to higher resolution impervious cover datasets.
- Static estimates (i.e., a snapshot of conditions in 2006) appear to be substantially more reliable than estimates of change between 2001 and 2006. This appears to be a function of (1) apparent lag between completion of construction and occupancy/recordation, (2) cases of change in housing units or employment not associated with construction activity (i.e., change in occupancy, change in building use, etc.), (3) lack of direct estimates of housing units and employment in 2001 (these must be estimated by interpolation or extrapolation), and (4) apparent insensitivity of the NLCD 2001-2006 impervious cover change dataset to detect small-scale distributed changes in impervious cover. This scale of change is often associated with urban infill development.

Exhibits and discussion related to this analysis are provided in Appendix B.

2.3.3 Preliminary Findings from Correlation Analyses

Scatter plot matrices (SPLOMs) and Spearmans's Rho correlation statistics were developed for approximately 20 parameters for 5 different query subsets of the preliminary analysis dataset. Exhibits from this analysis are provided in Appendix B. The intent of this analysis was to better understand the relative strength of correlations between potential independent and dependent model parameters and develop initial recommendations for the form of the regression model.

In general, the correlation trends of CBG attributes in the preliminary analysis dataset were consistent with what is logically expected. For example, denser development is logically expected to be correlated to higher accessibility metrics (i.e., more centrally located CBGs). However, relatively weak correlations were observed between many parameters and metrics related to *change in* impervious cover (2001 to 2006) indicating that no one attribute can explain the majority of variability in impervious cover change among the CBGs. Much stronger correlations were observed between potential independent parameters and the snapshot estimate of impervious cover in 2006.

The parameter with the strongest correlation to impervious surface growth rates (i.e., change in imperviousness per change in units of development) appears to be the static estimate of the overall imperviousness of the CBG. This is expected for a number of reasons: (1) imperviousness is limited by an upper bound (100 percent), (2) the net increase in impervious cover associated with a new or redevelopment project is theoretically less on average when the existing impervious cover of the site is already high; in other words, if impervious cover is replaced by new impervious cover (e.g., a 20-story building replacing a 3-story building), this does not contributed to net ISG, and (3) denser new/redevelopment tends to occur in geographic regions where existing development is more intense; in other words, the current intensity development in a place is a logical indicator of the intensity of development that will occur.

It was observed that CBG static imperviousness was strongly correlated to housing density and employment density, and somewhat less strongly correlated to other SLI sub-metrics. This indicates that the analysis dataset could potentially provide a robust prediction of impervious cover based on parameters related to housing unit density and employment density alone.

Also, it was noted that there are many CBGs that experienced no change in imperviousness as estimated by NLCD 2006. Therefore for metrics related to change in imperviousness, the dataset is dominated by zero values. Zero is potentially a real result, so it is not reasonable to filter the dataset to exclude zeros. However, the overwhelming presence of zero values appears to limit the ability to develop strong correlations. It also prevents meaningful log transformation without positive translation (i.e., positively adjusting all values to ensure no zeros before transforming).

2.4 Model Selection Recommendations

Based on the results of the preliminary analyses described above, resolutions were obtained for the key decision points introduced in Section 2.2.

- **Is a functional or logical regression more appropriate for used in the ISGM?** Both functional and logical regression models have been used previously to characterize impervious cover as a function of land development quantities (California OHHEA, 2010; USEPA, 2009). Functional models can be used for relatively small datasets up to very large datasets and are the most commonly employed type of regression model. Independent variables are inserted into the mathematical function to yield an estimate of the dependent variable. Logical regression models are capable of representing more complex relationships, and are especially useful where discontinuities (i.e., stepwise functions) or non-monotonic relationships are expected in the prediction. A larger dataset is generally needed to support a logical regression and often subjective "rules" must be developed for handling different conditional variables. For this analysis, a functional regression was preferred because (1) a continuous, monotonic trend is expected in the relationship between the dependent and independent variables, (2) this approach allows a wider range of potential sample sizes to be used and therefore does not constrain other decision factors, and (3) this type of regression is more common than a logical regression and is more easily communicated to a broad user group.

- **Is it more reliable to base the ISGM on change estimates or static estimates?** A regression based on change metrics would more directly support the estimation of net impervious surface growth (net ISG). However, based on the discussion provided in Section 2.3, a model based on static estimates was considered to be more reliable for the ISGM than one based on change estimates:
    - Static estimates appear to have lower levels of relative error than change estimates, which largely is due to the fact that over 5 years there does not appear to be enough change in development to statistically detect a change in imperviousness.
    - Static estimates can more readily be refined and validated using supporting datasets such as higher resolution impervious cover datasets where available. In contrast, in order to refine or validate estimates of change metrics, high resolution supporting datasets are required two points in time, which are less commonly available.
    - Using static estimates requires less subjectivity regarding the sub-sampling of the dataset to isolate CBGs that experienced significant development/redevelopment in the window of observations (2001 to 2006)
- **What scale and resolution of remote sensing analysis best balances data quality and data quantity to yield the most reliable model?** Based on observations of data quality and reasonableness (Section 2.3), a broad analysis was strongly preferred: (1) a broad range of potential independent variables (e.g., development density, destination accessibility) are likely to be needed to adequately describe the urban context, (2) regional variability may need to be considered in this or future analyses and can be much more rigorously supported by analyzing a large number of samples, and (3) observations of data quality and reasonableness discussed in Section 2.3 indicate that the datasets that would be used in the broader analysis appear to have adequate quality and reliability.

The ISGM described in Section 3 incorporates these recommendations.

3. MODEL DESCRIPTION AND RESULTS

3.1 Form of Impervious Surface Growth Model

The ISGM is based on a multivariate, non-linear regression equation that yields an estimate of average imperviousness based on the housing unit density, employment density, and destination accessibility of the unprotected areas of each CBG. This estimate of imperviousness can be multiplied by the unprotected acreage of the CBG to yield an estimate of the acreage of impervious cover in the unprotected area of each CBG. The hypothetical addition of development units (i.e., housing units and/or number of employees) results in adjustments to the independent parameters (i.e., increased housing unit density and/or increased employment density) in the regression, which yields an increase in the impervious cover estimated by the regression. The difference in impervious cover predicted between the baseline condition and the hypothetical adjusted condition can be attributed to the hypothetical number of units of development added. This model is conceptually illustrated in Figure 1 below.

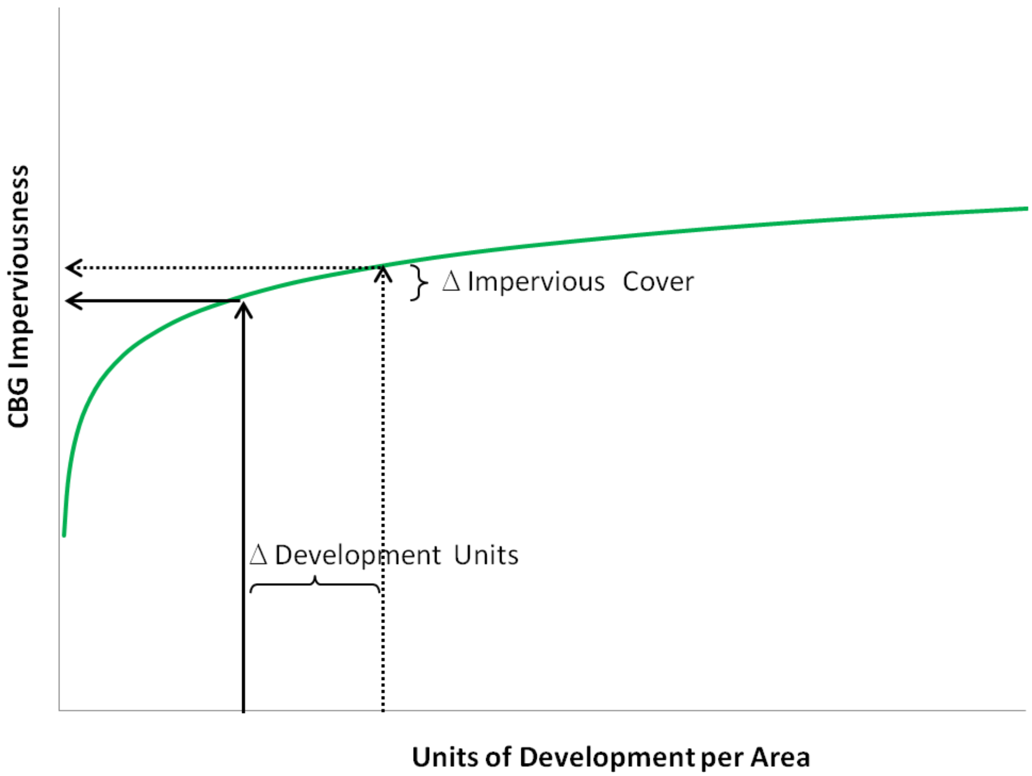


Figure 1. Conceptual Model for Estimation of Impervious Cover Change

This form of model was selected based on the factors discussed in Section 2.4. The form is believed to be well suited for the intended application of the ISGM.

3.2 ISGM Regression Analysis

The regression equation selected for use in the ISGM was chosen from a large number of potential options based on an iterative and adaptive process. This section summarizes the approach that was used to develop the regression.

First, the entire sample of 206,701 CBGs in the conterminous United States that contain unprotected land area was filtered to exclude CBGs that do not contain sufficient and consistent data upon which to base the development of the regression. CBGs were excluded if they were not fully covered by the LEHD (CT, DC, MA, NH) employment dataset, or for which LEHD 2006 employment estimates deviated too substantially from the employment estimates from

2009 reported by the SLI database (LA, ME, MT, ND, NE, OK, SD, WI, WV). A threshold ratio of 87 percent (2006 LEHD/2009 SLI) represents the 80th percentile value and is intended to exclude states where significant amount of workers were not accounted in the LEHD surveys. These CBGs were not considered reliable as the basis for developing the regression equation and it was not necessary to include them to yield an adequately large and robust sample set. The resulting CBG dataset used for analysis included 181,809 CBGs, each containing consistent estimates of the key independent and dependent parameters. The dataset used for the regression analysis is described in Table 2.

Table 2. Dataset Used for Regression Analysis

Field ID	Units	Description	Source
CBG	text	12 digit identification number of each CBG	SLI 2009 (Theobald et al, 2011)
ST_ABBREV	text	Two-letter state abbreviation	SLI 2009
MSA	text	Metropolitan Statistical Area Name	SLI 2009
UNP_AC_06	acres	Total unprotected area	Geosyntec analysis of unprotected areas using PADUS v1.2, Navteq and NLCD (See Appendix A)
HU2006	hu	Occupied housing units (2006)	US Census Bureau, obtained from USEPA
EMP2006	emp	Total employees; non-federal (2006)	LEHD (downloaded February 2011)
IMP2006	acres	Impervious acres in unprotected area (2006)	[06_PCTIMP_UNP] × [UNP_AC_06]
06_PCTIMP_UNP	%	Percent impervious cover in unprotected areas	Geosyntec analysis of unprotected areas and NLCD 2006 impervious cover dataset (See Appendix A)
06_HU_UAC	hu/ac	Unprotected area housing unit density	[HU2006]/[UNP_AC_2006]
06_EMP_UAC	emp/ac	Unprotected area employment density	[EMP2006]/[UNP_AC_2006]
D5AR	index	Destination accessibility, residential perspective (D5ar)	SLI 2009
SGMRANK	integer	Strength of State Growth Management Policy	"Getting Back on Track" (Bhatt et al, 2009)

Note: Various other parameters were evaluated as part of potential regression models that were not selected.

The analysis dataset was then stratified into 5 equal interval bins from 0 to 100 percent impervious cover, and an equal number of random samples were selected from each bin. This practice of "stratified random sampling" helps improve the reliability of the resulting regression equation by ensuring that certain ranges of predictions are not over-represented in the regression analysis. For example, the CBG dataset is more heavily weighted toward CBGs between 30 and 60 percent imperviousness than CBGs at lower or higher ranges of imperviousness. Without stratified sampling methods, the resulting regression model could tend to fit the 30 to 60 percent impervious CBGs region of the prediction better than other regions thereby potentially producing poor results for imperviousness estimates outside of this range. After stratified random sampling, the resulting subset is more evenly distributed across the full range of possible imperviousness predictions. Stratified random sampling conducted to develop the regression model yielded approximately 25,129 samples (i.e., ≈5,000 data points per imperviousness bin) in 37 states.

Using this subsample dataset, many model trials were conducted using different forms of regression equations and different combinations of potentially significant explanatory variables. The nonlinear regression modeling tool in SYSTAT© Version 12 (http://www.systat.com/) was employed to find the best combination of coefficients for each trial and generate regression statistics. These statistics were evaluated along with an inspection of scatter plots of the predicted imperviousness versus measured imperviousness (NLCD 2006) for each trial. Based on feedback from previous trials, subsequent trials were adapted in attempt to improve the model fit and reliability:

- Where the resulting confidence interval of a model coefficient for an explanatory variable spanned zero, that variable did not significantly contribute to the prediction of imperviousness and therefore was removed or applied differently within the equation.
- Where the relative sensitivity of an explanatory variable was much less than others and did not perceptibly improve the fit of the regression, the variable was removed or applied differently within the equation.
- Where the scatter plot of predicted versus measured imperviousness was nonlinear (i.e., residuals were not evenly distributed across the range of predictions), explanatory variables were transformed to achieve a more linear fit.

Based on these trials, a best performing regression equation was identified. The determination of “best performing” was based on best professional judgment based on inspection of regression statistics (i.e., sum of squared residual, significance of coefficients), and the degree of linearity of fit between observed and predicted imperviousness. While further refinements to this equation may be made through additional analysis, this equation is considered reliable for the intended application of the model and understanding that model predictions are imperfect.

3.3 Best Performing Regression Equation

The best performing non-linear regression model that was obtained has the following form:

$$\%IMP = \frac{100}{1 + \frac{1}{a_0 + a_1 HU_{UAC} + a_2 EMP_{UAC} + a_3 D5AR}}$$

Where:

%IMP is percent imperviousness of the unprotected area of the CBG

HU_{UAC} is the housing units per unprotected acre
EMP_{UAC} is the employees per unprotected acre
$D5AR$ is number of jobs within one hour travel time based on a gravity model (Theobald et al., 2011)
a_0, a_1, a_2, a_3 are model parameters

The form of this equation was identified from iterative feedback, based on the known bounds of the prediction interval (0 to 100) and the observation that the relationship between percent imperviousness and the natural logarithm of housing units per unprotected acre, HU_{UAC}, tended to have an S-curve shape. The number of employees per unprotected area, EMP_{UAC}, and destination accessibility (D5Ar) also showed similar relationships with percent imperviousness. Therefore, an equation was developed that asymptotically approached 100% while considering the weight each one of these variables had on the total percent imperviousness.

Exhibit 1 reports SYSTAT© code and regression statistics for the best performing regression equations, and Figure 2 shows the comparison of estimated versus observed. While the independent variables have different relatively degrees of influence in different ranges of the prediction space, each was found to be significant at a 95th level of confidence.

Exhibit 1: SYSTAT Code and Regression Statistics for Best Performing Equation

```
SELECT (WEIGHT = 1) AND (A06_PCTIMP_UNP > 0)  AND (A06_PCTIMP_UNP < 100)
AND ((A06_HU_UAC > 0) OR (A06_EMP_UAC > 0) OR (D5AR>0))
NONLIN
WEIGHT
MODEL A06_PCTIMP_UNP = 100/(1+1/(a0+a1*A06_HU_UAC+a2*A06_EMP_UAC+a3*D5AR))
ESTIMATE / GN ITER = 300
```

Sum of Squares and Mean Squares

Source	SS	df	Mean Squares
Regression	74,755,817	4	18,688,954
Residual	3,605,966	25,125	143.5
Total	78,361,783	25,129	
Mean corrected	20,588,759	25,128	

R-squares

Raw R-square (1-Residual/Total) : 0.954
Mean Corrected R-square (1-Residual/Corrected) : 0.825
R-square(Observed vs Predicted) : 0.827
R (correlation coeff.) 0.909

Parameter Estimates

Parameter	Estimate	ASE	Parameter/ASE	Wald 95% Confidence Interval	
				Lower	Upper
A0	0.008	0.002	3.962	0.004	0.012
A1	0.123	0.0012	99.517	0.120	0.125
A2	0.093	0.0013	70.462	0.090	0.096
A3	7.39e-7	1.4e-8	51.075	7.11e-7	7.67e-7

Using the best fit coefficients from this analysis, the regression model is expressed as:

$$\%IMP = \frac{100}{1 + \frac{1}{0.008 + 0.1227 \times HU_{UAC} + 0.093 \times EMP_{UAC} + 0.000000739 \times D5AR}}$$

Where: %IMP is percent imperviousness of the unprotected area of the CBG
HU_{UAC} is the housing units per unprotected acre
EMP_{UAC} is the employees per unprotected acre
$D5AR$ is number of jobs within one hour travel time based on a gravity model

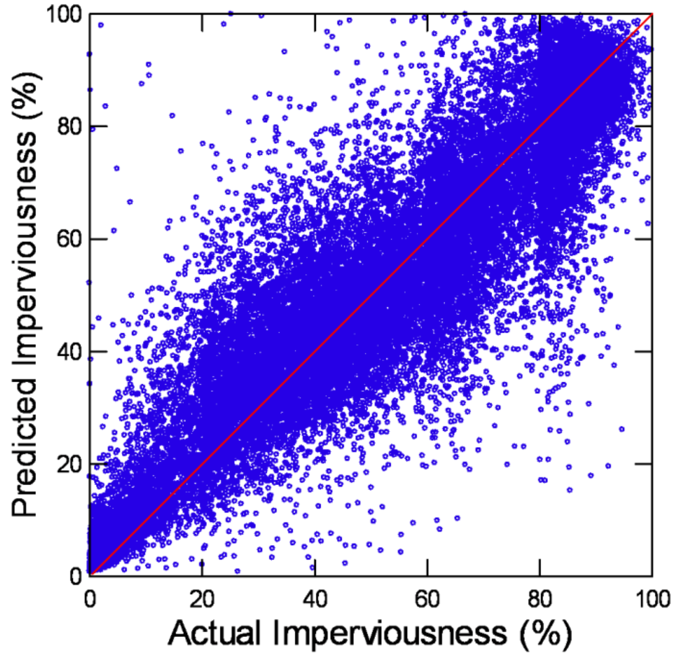


Figure 2. Comparison of Predicted to Proposed Imperviousness, Development Subsample

3.3.1 Discussion

The regression equation is depicted graphically in Figure 3. The sensitivity of housing density, employment density, and destination accessibility (D5Ar) are illustrated in Figure 4, Figure 5, and Figure 6, respectively. The following observations can be made about this regression:

- The regression equation is appropriately constrained between 0 and 100 percent imperviousness and provides an approximate linear fit between predicted and measured imperviousness.
- The parameter with the strongest influence on imperviousness is housing density, although employment density has a similar degree of influence. These parameters are understood to vary independently of each other, therefore necessitating the inclusion of both.
- Destination accessibility is less influential except in CBGs with relatively low housing and employment density. In the case of a CBG with low development density but high destination accessibility, the "background" imperviousness is higher. This effect is believed to be most important for CBGs in close proximity to larger cities that can be dominated by transportation infrastructure and partially occupied industrial landscape where housing and employment density are not sufficient to predict the high level of imperviousness expected.

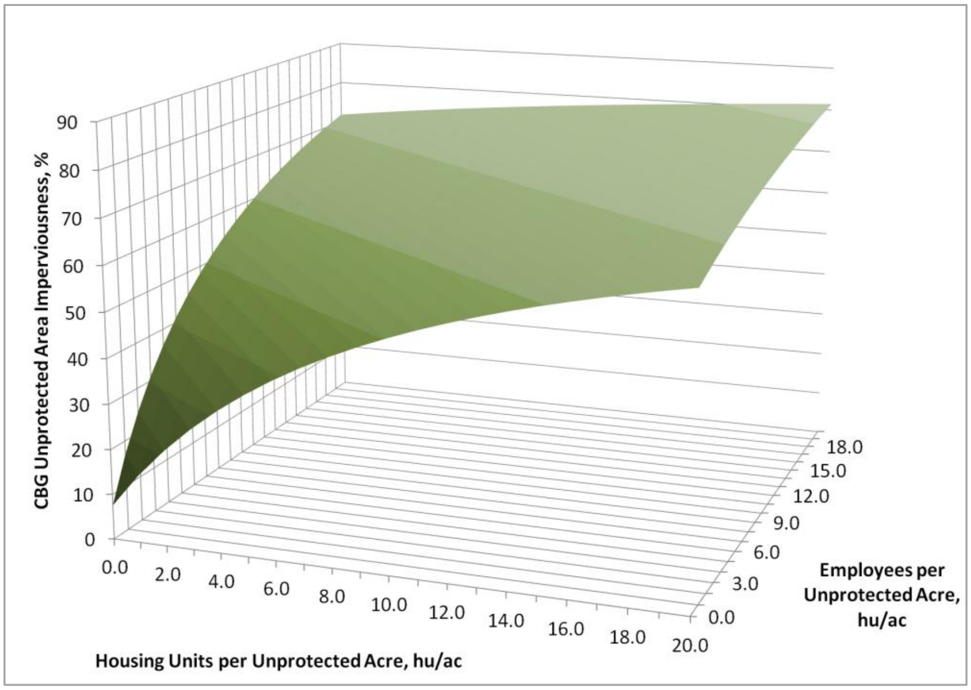


Figure 3. Partial Graphical Depiction of Selected Regression Model (D5Ar = 100,000)

Figure 4. Selected Regression Model Sensitivity to Housing Density (D5Ar = 100,000)

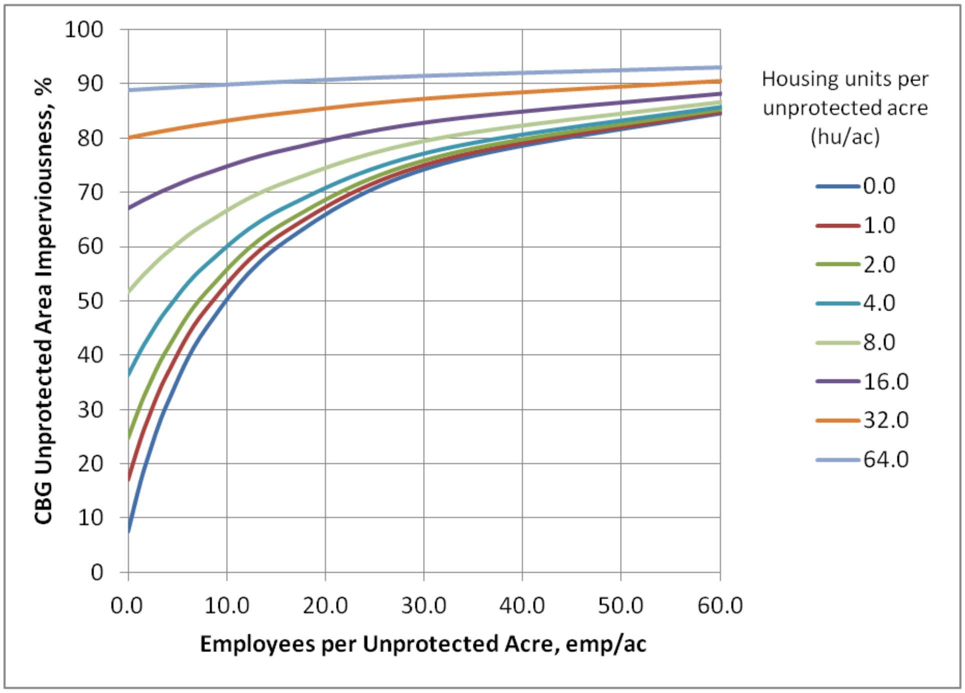


Figure 5. Selected Regression Model Sensitivity to Employment Density (D5Ar = 100,000)

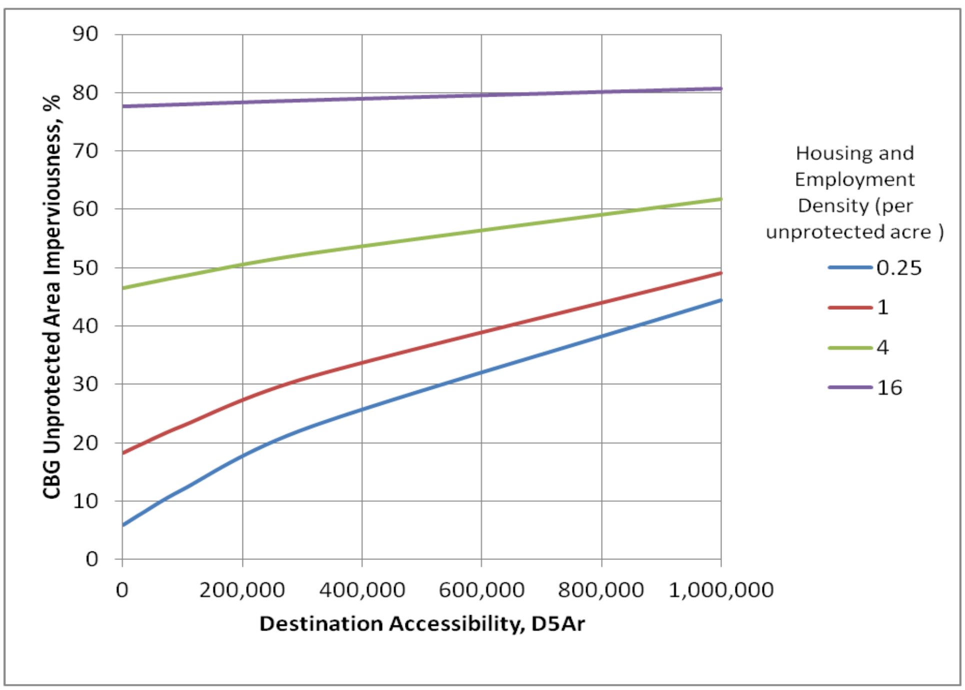


Figure 6. Selected Regression Model Sensitivity to Destination Accessibility (D5Ar)

3.4 Model Validation

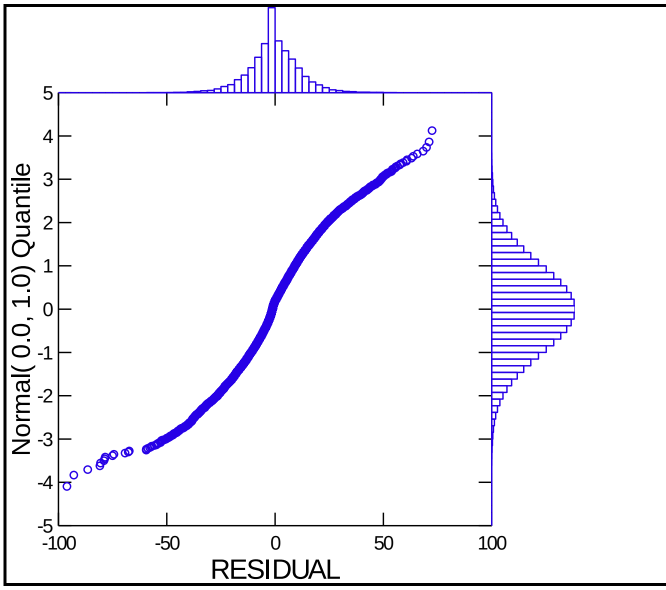
The model was validated in three primary ways:

1) Application of the selected regression equation to the remainder of the analysis dataset that was not used in the development of the regression model.
2) Comparison of the fit of the selected regression equation to the results of a similar recent effort to describe relationships with impervious cover.
3) Application of the ISGM to a random subset of CBGs coupled with inspection of aerial photographs to evaluate reasonableness.

The results of these validation efforts are presented and discussed below.

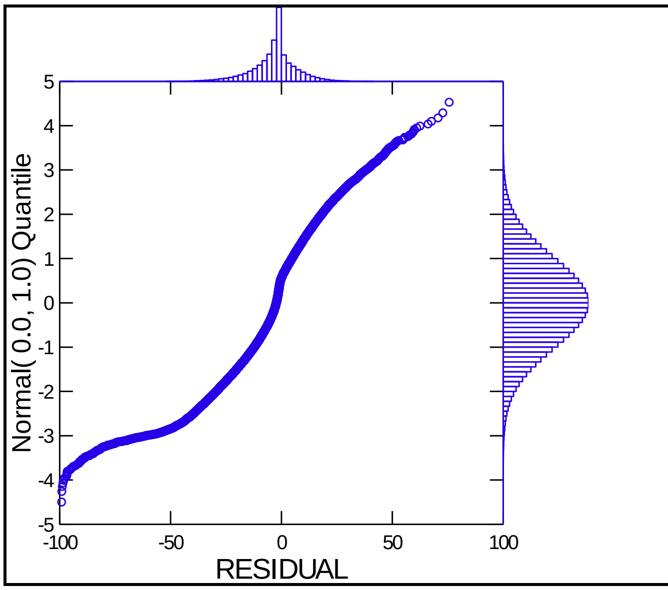
3.4.1 Application to Remaining Sample Data

The selected regression model was applied to the remaining 156,520 samples (CBGs) that were not used in the development of the model. This validation was based on a comparison made between the residuals of the model development dataset (25,129 CBGs, Figure 7) and the residuals of the remaining dataset (156,520 CBGs, Figure 8). Residuals are fairly evenly distributed for both datasets, and the mean and median of residuals differ by only 1 to 2 percent imperviousness between the datasets – the standard deviations differ by less than 1 percent. These differences can likely be attributed to the greater influence of the middle of the range of imperviousness (30 to 60 percent) in the full dataset compared to the stratified model development subsample, as well as the presence of potential outliers. The Anderson-Darling test was used to check the normality of the residuals. As indicated by the p-values less than 0.05, the residuals do not statistically follow a normal distribution at a 95% significance level. However, with such a large number of data points only a small deviation from normality will result in rejecting the null hypothesis that the sample arise from a normally-distributed population. A truly normal distribution will have a skewness of zero and kurtosis of three. As shown in Figure 7 the skewness is only slightly negative and the kurtosis is slightly higher than three. While normally-distributed residuals are preferred in regression analysis, residuals that are approximately normally and have approximately constant variance indicates that the regression equation will produce reasonably accurate predictions (Helsel and Hirsch, 2002). This comparison indicates the model development subsample is a reasonably representative of the full population.



	RESIDUAL
N of Cases	25,129
Minimum	-95.753
Maximum	72.777
Median	-0.821
Arithmetic Mean	-0.543
Standard Deviation	11.967
Skewness(G1)	-0.061
Kurtosis(G2)	3.080
Anderson-Darling Statistic	201.184
Adjusted Anderson-Darling Statistic	201.190
p-value	<0.01

Figure 7. Residual Statistics for Data Used in Regression Model



	RESIDUAL
N of Cases	156,520
Minimum	-98.817
Maximum	75.949
Median	-1.920
Arithmetic Mean	-3.144
Standard Deviation	10.896
Skewness(G1)	-0.700
Kurtosis(G2)	5.094
Anderson-Darling Statistic	29,289
Adjusted Anderson-Darling Statistic	29,289
p-value	<0.01

Figure 8. Residual Statistics for Remaining Data Not Used in Regression Model

3.4.2 Comparison to Similar Effort

The relative error, variability, and magnitude of predictions from the best performing regression equation were compared to a recent comparable effort by the State of California (California OEHHA, 2010). The California analysis used high resolution remote sensing of randomly selected neighborhoods in several cities to estimate the imperviousness of a range of land uses in California. The sample set included over 330 residential neighborhoods at densities ranging from

1 to 50 du/ac as well as a variety of other neighborhoods that were not classified by an analogous density metric. Among other outcomes, the analysis yielded a regression equation that can be used to correlate land use imperviousness to housing unit density. Figure 9 shows the plot of imperviousness versus housing unit density derived from this analysis. For comparison, the ISGM regression model is overlaid on this chart (holding employment at 0 and D5Ar at the approximate median value of 100,000).

While these regressions are not directly comparable (CBGs are generally at a larger scale and less homogenous than the neighborhoods surveyed), the relative magnitudes and shapes are similar. The ISGM equation appears to fit the California data fairly well, and the regression statistics of the ISGM equation (based on fit to nationwide CBGs) compares favorably to the best fit that was found for the California ISC analysis (based on California neighborhoods). In addition, it is noted that the CA equation potentially returns values that are less than 0 and greater than 100 percent if applied outside of its range while the ISGM equation is constrained between these bounds.

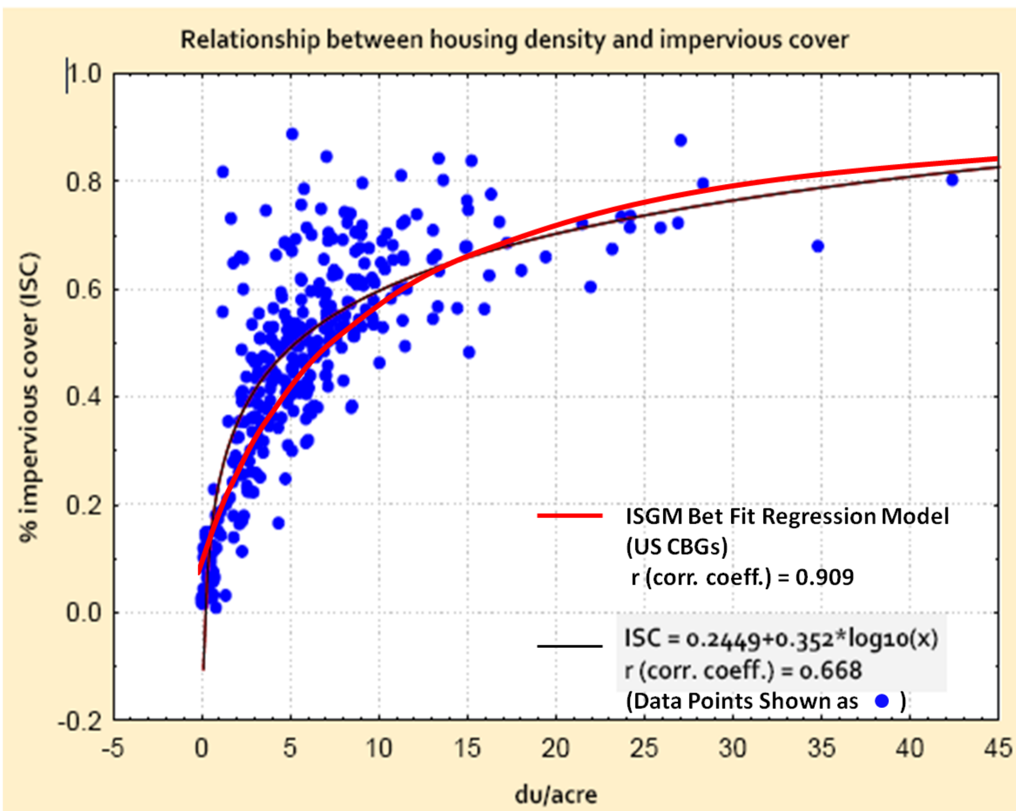


Figure 9. Comparison of ISGM Results to California ISC Analysis

Note: the correlation coefficient for the ISGM best fit regression model is based on its fit to the selected subsample of nationwide CBGs for comparison; it is not based on the California land use data that is plotted on this chart.

3.4.3 Reasonableness Inspection of ISGM Predictions

The ISGM was applied to a subset of CBGs to predict the net ISG associated with hypothetical increases in housing units and employees. Twenty-four CBGs from five US cities were studied. These CBGs were selected prior to application of the model to represent a cross section of CBGs from different locations within the urban context (i.e., downtown vs. suburban), different city sizes, and states with different land use management policies. Net impervious surface growth per additional unit of development was estimated based on a nominal increase in development units of 100 units. (Note, any magnitude of increase can be evaluated in the model; 100 was selected for the purpose of evaluating reasonableness). Exhibits of each CBG evaluated are shown in Appendix C.

This inspection showed that results are reasonable and followed expected trends. Of the CBGs inspected, the net residential ISG ranged from approximately 4,000 sq-ft per housing unit in urban fringe CBGs to approximately 200 sq-ft per housing unit in highly urbanized CBGs. Net employment ISG followed a similar trend to net residential ISG with somewhat lower values predicted. This is expected based on the form of the regression equation and appears to yield reasonable results in the CBGs inspected.

While the magnitudes are reasonable, specific examples were observed where the regression may not fully describe the expected variability.

3.4.4 Summary of Validation and Limitations

Overall, the ISGM appears to be a valid basis for estimating net ISG across a wide range of urban conditions. While the model may over-predict or under-predict imperviousness at a CBG level, it appears to provide a reasonably reliable estimate of relative net ISG, on average, in the areas of cities where development most commonly occurs. However, four key limitations should be understood in applying the model:

- First, the model is limited in accounting for impervious surfaces that did not support housing or employment in 2006. CBGs with a proportionately large fraction of impervious surface dedicated to transportation or to under-occupied structures would tend to be biased toward lower estimates of static imperviousness than was actually present. This has the effect of predicting greater net ISG with added development units than would actually be expected and could result in some systematic bias when evaluating proposed development projects in inner-city locations that have significant transportation components or under-occupied structures. In these cases, the net ISG of under-occupied inner city areas could tend to be over-estimated.
- Second, the model does not directly account for the effect of growth management policies on the prediction of net ISG. While this factor could potentially be evaluated further in future studies, the current level of information regarding growth management policies is not believed to be sufficiently standardized and normalized to serve as a predictive variable (See further discussion in Appendix B). It is expected that the application of the

ISGM would be supported by regional forecast models to identify the location (i.e., the CBG ID) where development would have otherwise gone. These models would explicitly account for growth management policies to identify the alternative location thereby accounting in part for the effect of the applicable growth management policy. However, the ISGM may not fully account for the occurrence of higher density development at the urban fringe in regions where such development patterns would be driven by growth management policies (i.e., urban growth boundaries, etc.) This may cause the ISGM to overestimate net ISG at the urban fringe where growth management policies are strong and effective or there are economic drivers for this growth that are not accounted for in the ISGM.

- Third, the model does not directly account for impervious area added beyond the borders of a given CBG due to infrastructure expansion to support the growth within the CBG (i.e., a an urban freeway widening to accommodate growth in suburbs, or an extension of a roadway within one CBG reach development in another CBG). This would tend to result in minor underestimation of impervious surface growth attributed to development in CBGs at the urban fringe, and may result in minor overestimation of impervious surface growth in areas closer to city centers.
- Finally, the model is believed to be less reliable for CBGs in Alaska and Hawaii because of weaker in input datasets for these states. First, the NLCD impervious cover dataset did not cover Alaska and Hawaii at the time of this analysis, therefore the analysis dataset upon which the regression was developed did not include CBGs from Alaska and Hawaii. Second, the SLI database (Theobald et al., 2011) does not contain values for destination accessibility (D5ar) for Alaska and Hawaii. The model can still be applied without D5ar, however, the effect of setting D5ar to 0 (where it is known to be non-zero) would be a tendency to underestimate the difference in ISG between locations with higher accessibility versus lower accessibility. In other words, the tool would tend overestimate ISG for a given quantity of development in both cases, but would tend to overestimate ISG by a greater relative amount in areas where accessibility is actually high (i.e., urban areas) than in areas where accessibility is actually lower (i.e., urban fringe). Therefore the difference in ISG predicted in Alaska and Hawaii would tend to be somewhat biased but would generally be conservative when comparing the impacts of a quantity of growth at a brownfield site (generally higher accessibility location) to the same quantity of growth in at an alternative site (generally lower accessibility).

No other potential sources of systematic bias were identified in the model validation efforts.

3.4.5 Recommendations for Further Analysis

While the ISGM is considered to be reliable for its intended application, there is potential to refine the model based on further analysis and validation efforts. Potential opportunities for further analysis include:

- Evaluation of different regression models for different geographic regions or different regions within the urban context. For this analysis, it was considered to be desirable to develop a single universal equation that could be applied across all CBGs. The resulting universal equation achieved favorable regression statistics, therefore segmentation of the dataset was not considered to be warranted. However, the regression could potentially be improved via segmentation.

- Evaluation of logical regression models. A further analysis could consider the alternative pathways offered by logical regression models to describe the same dataset.
- Evaluation of multiple categories of jobs. For example, it may improve the regression model to include commercial and industrial jobs as separate inputs to the ISGM.
- Evaluation of land value metrics. The direct consideration of improved land value was beyond the scope of this analysis; however incorporating more direct economic considerations could improve the regression.
- Evaluation of an alternative residential density accessibility factor (D5Ar) based on shorter commuting distances or a higher coefficient of degradation in the gravity model. In many urban areas, it may be possible to reach the urban fringe in 30 minutes or less. Therefore, it may be appropriate to use a shorter distance or a higher degradation coefficient in a gravity model to better account for the effect of destination accessibility on anticipated development intensity.

3.5 ISGM User Interface

A user interface for the ISGM has been developed to provide access to the ISGM algorithms and to facilitate evaluation of the predicted effect of proposed development on net ISG in CBGs.

3.5.1 Description of Interface

The interface consists of a form in Excel 2007 with fixed columns and an expandable number of rows. Each row can be used to estimate the net ISG based on a user-defined CBG and a user defined increase in units of development. Table 3 describes the fields in the tool and the algorithms used to return the estimated value.

3.5.2 Intended Use of Interface

The ISGM User Interface is intended to allow bulk entry of CBG development scenarios and return estimates of the net ISG associated with each scenario:

1) User enters CBG ID and quantities of added development for each CBG to be analyzed.
2) Interface returns the estimated net ISG.
3) Interface returns qualifiers or notes relative to the result, if applicable.

The interface supports copy and paste of lists of CBGs and development quantities into the respective fields. The current version supports up to 25,000 CBGs.

Table 3. ISGM User Interface Fields

Field Type	Field ID	Field Description	Units	Source
User Input	CBG	CBG ID	text	User entered
	MSA	Metropolitan statistical area	text	Returned via lookup from ISGM Database based on CBG ID Primary Key
	ADD_HU	Added Housing Units	hu	User entered
	ADD_EMP	Added Employment Units	jobs	User entered
CBG Baseline Conditions	UNP_ACRES	Best estimate of unprotected area, ac	ac	Returned via lookup from ISGM Database based on CBG ID Primary Key
	HU_DENS	Housing Unit Density (unprotected, baseline, 2010)	hu/ac	Returned via lookup from ISGM Database based on CBG ID Primary Key
	EMP_DENS	Employment Density (unprotected, baseline, 2009)	jobs/ac	Returned via lookup from ISGM Database based on CBG ID Primary Key
	D5AR	Residential Destination Accessibility (D5Ar, baseline, 2009)	jobs	Returned via lookup from ISGM Database based on CBG ID Primary Key
Development-adjusted CBG Conditions (Adjusted)	HU_DENS_ADJ	Housing Unit Density (unprotected, adjusted)	hu/ac	Calculated based on 2010 conditions plus user entered number of added housing units
	EMP_DENS_ADJ	Employment Density (unprotected, adjusted)	jobs/ac	Calculated based on 2009 conditions plus user entered number of added jobs
	D5AR_ADJ	Residential Destination Accessibility (D5Ar, adjusted)	jobs	Calculated based on 2009 D5ar plus user entered number of added jobs
Results	ISG_NET	Net Impervious Surface Growth	ac	{ISGM IMP (Adjusted) - ISGM IMP (Baseline)}
	ISG_MAX	Maximum Possible Impervious Surface Growth in 2006	ac	Remaining pervious surface in CBG (NCLD 2006). Value displayed if ISG_NET > ISG_MAX
	QUAL	Qualifier	text	Returns qualifying information where model predictions as applicable.
	NOTES	Notes about results	text	Returns notes, as applicable.

ISGM IMP (Baseline) = CGB unprotected area impervious area predicted for the baseline (2009/2010) condition based on the ISGM regression equation using the baseline independent input variables.
ISGM IMP (Adjusted) = CGB unprotected area impervious area predicted for the development-adjusted condition based on the ISGM regression equation using the development adjusted independent input variables.

3.5.3 Final Supporting Dataset

Table 4 describes the fields in the final dataset that is packaged with the ISGM User Interface and supports the estimation of net ISG. For the release of the tool, estimates of baseline housing unit and employment density were updated using more recent sources than those used to develop the ISGM model. This update and future updates are supported by the model and are recommended to improve reliability. Update of the underlying regression equation is not necessary as the regression relationships were based on synchronous (2006) estimates of independent and dependent variables, and these underlying relationships are not generally expected to change substantially with time in the foreseeable future.

Table 4. ISGM Supporting Database

Field ID	Units	Description	Source
CBG	text	12 digit identification number of each CBG	SLI 2009 (Theobald et al, 2011)
ST_ABBREV	text	Two-letter state abbreviation	SLI 2009
MSA	text	Metropolitan Statistical Area Name	SLI 2009
UNP_ACRES	acres	Best available estimate of unprotected area (filled from multiple sources based on logic)	Primary: UNP_AC_06 Alternate 1: ACRE_PRIV; used in AK and HI only Alternate 2: LAND_AC; used in cases where UNP_AC_06 not available, and in AK and HI where ACRE_PRIV not available
HU_DENS	hu/ac	Best available estimate of unprotected area housing unit density	[HU2010]/[UNP_ACRES]
EMP_DENS	emp/ac	Best available estimate of unprotected area employment unit density	[EMP2009]/[UNP_ACRES]
D5AR	index	Destination accessibility, residential perspective (D5ar)	SLI 2009
Supporting Data			
UNP_AC_06	acres	Total unprotected area	Geosyntec analysis of unprotected areas using PADUS v1.2, Navteq and NLCD (See Appendix A)
HU2010	hu	Occupied housing units (2010)	US Census Bureau, obtained from USEPA; filled with data from SLI 2009 where 2010 est. not available
EMP2009	emp	Total employees (2009)	SLI 2009
IMP2006	acres	Impervious acres in unprotected area (2006)	Geosyntec analysis of unprotected areas and NLCD 2006 Imp Cover
ISG_MAX	acres	Remaining pervious area in catchment (2006)	[UNP_AC_06] – [IMP2006]
LAND_AC	acres	Total CBG Land Area (non-water), acres	US Census Bureau, ALAND00, obtained from USEPA
ACRES_PRIV	acres	CBG Private Area, acres	SLI 2009

3.5.4 Adjustments to Supporting Database Based on Reasonableness Inspection

As described in Appendix A and above, when calculating gross housing and employment density, efforts were made to refine the metric to reflect density in areas where development can occur (i.e., unprotected area). For instance, a block group that includes a large city park would appear to be much lower in density than it actually is if the area of the park is included in the analysis. Calculating the total area of the block group *excluding* the park provides a more realistic measure of density. Therefore two national datasets (Navteq, 2011; Protected Areas Dataset – US, PAD-US V1.2, April 2011) representing public and protected lands were analyzed to estimate the total land area of each block group that is privately owned and unprotected from development. Details of this analysis are provided in Appendix A.

There are some important limitations to the use of the PAD-US dataset to identify areas that are protected from development. For instance, some of the public lands in PAD-US are not necessarily protected from development. Many tribal lands and military bases fall into this category.[4] Likewise some of the public lands (including tribal and others) include housing and jobs. Therefore removing that land area from calculations of gross housing or employment density results in inaccuracies (sometimes quite significant inaccuracies).

In the use of PAD-US for this analysis, an initial level of screening was conducted based on the "Status" field. Features that were identified as "Designated – Legally or administratively decreed" were included, while features designated as "Not Known – Current site status unknown" or "Proposed – local government level approval" were not included. Further screening based on other fields in the PAD-US database would have likely improved the reliability of these data. After integration of the protected area datasets with housing and employment data, steps were taken to address the clearest examples of inaccuracies that resulted from the above limitations. These steps were intended to improve the reliability of the tool, and are described below.

After calculating housing density on privately owned unprotected land, quality checks were conducted to identify block groups with density metrics that appeared to be far outside the range of what reasonably could be expected.

1. *Identify CBGs with little or no privately-owned unprotected land AND houses.* This check was conducted to identify block groups that were more or less completely contained by public/conservation land but none-the-less had housing development on it. In these cases it was assumed that the land is not protected from development (e.g., tribal land) and adjusted the density measures to consider the entire land area of the block group. Two separate passes at the data were used to select block groups in this category:
    - <0.2 acres privately-owned unprotected land AND >1 housing unit
    - <1 acre privately-owned unprotected AND >10 housing units

[4] In retrospect, all tribal lands and military bases should *not* have been included as protected land type, due to the fact that people live and work on these lands.

2. *Identify block groups with high residential density AND relatively low destination accessibility.* Residential density above 20 units per acre is almost exclusively found in centrally located areas of large or medium-sized cities. Block groups that are *not* in such areas can be identified using a destination accessibility metric (called "D5ae") that counts the total number or working age adults living within 30 miles of a block group (gravity weighted so that population further away are counted less). In cases where high residential density was found in areas with low destination accessibility, it was assumed that at least some of the public land is not protected from development. Therefore the density measures were adjusted to consider the entire land area of the block group.[5] Two separate selection rules were used to identify block groups in this category:
    - >20 housing units per acre AND D5ae<75,000
    - >30 housing units per acre AND D5ae<200,000

3. *Identify block groups in Hawaii with high residential density (>20) AND quite large in total land area (>300 acres).* As noted above, destination accessibility metrics were not available for Hawaii. 65 total block groups on the island of Oahu were identified as high in residential density. Upon inspection, many of these were in the downtown area were such densities would be expected. Isolating only those block groups that were over 300 acres in area identified places that, upon spot checking, clearly did not have any residential density. Generally these block groups were on military bases where much of the land area is publicly owned. For all of these block groups, the density measures were adjusted to consider the entire land area of the block group.

4. *Identify block groups with very high residential density (>50) AND large in total land area (>200 acres). A* review of the density measures in a few very large metropolitan regions outside of HI revealed isolated examples of very high residential density in very large block groups far outside of city centers. Spot checking a few of these revealed that this unexpected result was due to a large portion of the total acreage being publically owned (e.g., a military base), yet homes are located in the publically owned area. This selection rule appeared to catch most, if not all, of these problems. For all block groups selected, the density measures were adjusted to consider the entire land area of the block group.

These criteria resulted in identification of approximately 420 CBGs (0.2% of total) for which the unprotected area was deemed to be unreliable. In these cases, the total land area of the CBG (LAND_AC) was used instead of the unprotected area for the purpose of computing density metrics.

[5] Note that destination accessibility metrics were not available for Alaska and Hawaii. The few block groups in AK were spot checked to confirm that they too were in low accessibility areas. Block groups in Hawaii were analyzed separately (see analysis procedure #3).

4. REFERENCES

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Appendix A: Datasets Considered for Analysis

Impervious Cover Datasets

Various impervious cover datasets were evaluated for their role in supporting the development of the ISGM. These datasets ranged from high resolution datasets to medium resolution datasets (Table A-1). While higher resolution impervious cover datasets can be more accurate, sub-pixel estimation methods used by the NLCD datasets have been improved and these datasets can provide reliable estimates of average imperviousness at the CBG scale.

Table A-1: Summary of Impervious Cover Datasets Considered for Analysis

Dataset/Extent	Details	Image Year	Source
National Land Cover Database 2001 Impervious Cover Layer	30m raster, estimates of composite imperviousness for each cell obtained based on sub-pixel methods.	2001	Multi-Resolution Land Characteristics Consortium (MRLC) (USGS, NOAA, and EPA)
National Land Cover Database 2006 Impervious Cover Layer and 2001/2006 Impervious Change Layer	30m raster, estimates of composite imperviousness for each cell obtained based on sub-pixel methods. Estimates of change in imperviousness between 2001 and 2006	2006	Multi-Resolution Land Characteristics Consortium (MRLC) (USGS, NOAA, and EPA)
State of Massachusetts	0.5m raster; available for free public use	2005	State of Massachusetts , GIS Department
State of Maine	5m raster, available for free public use	2004	State of Maine, GIS Department
Hawaiian Islands (Kauai, Hawaii, Oahu)	2.5m; available for free public use	2007	State of Hawaii, Office of Planning
Delaware County-wide Studies	0.25m; available for free public use. (Kent County, New Castle County, Sussex County)	2007	State of Delaware, Office of Management and Budget
City of Atlanta	Unknown resolution; differentiates between roofs, roads and other 4 other surface categories	Unknown	City of Atlanta
Portland Metro Area, High Resolution Land Cover	1m; raster available for free public use	2007	Oregon Metro
City of Durham, NC	Sub -2.5 m resolution; differentiates between roofs and paved areas. Obtained. Does not include right of way impervious area.	2010 (and potentially earlier dates)	City of Durham, NC
King County, WA	1m; cost: $305	2008	King County GIS
Santa Barbara County, CA	1m; available to Geosyntec	2006	Santa Barbara Project Clean Water

NCLD 2006 impervious datasets were analyzed using zonal statistics features in the ArcGIS Spatial Analyst Extension and the stand-alone STARSPAN program (Rueda, C.A., Greenberg, J.A., and Ustin, S.L. StarSpan: A Tool for Fast Selective Pixel Extraction from Remotely Sensed Data. (2005). Center for Spatial Technologies and Remote Sensing (CSTARS), University of California at Davis, Davis, CA.)

High Resolution Imagery

Various sources of high resolution visible spectrum (RGB, single spectrum sensor) and multi-spectral imagery datasets were evaluated for potential application to this project. A brief summary is provided in Table A-2.

Table A-2: Summary of Imagery Datasets Considered for Analysis

Dataset/Extent	Details	Image Year	Source
National Agricultural Imagery Program	1m or finer resolution; some regions have multi-spectral bands	Generally 2009	USDA
Bing Maps/Nationwide	RGB images; dynamic resolution to sub-meter	Generally 2010/11	Microsoft Corp.
Virtual Earth/Nationwide	RGB images; dynamic resolution to sub-meter	Generally 2010/11	ESRI licensed data stream
Google Earth/Nationwide	RGB images; dynamic resolution to sub-meter	Generally 2010/11	Google
Custom Order Multi-spectral Imagery	Various image providers; costs on a per "scene" basis	Varies	Various
Historic Repositories/ Unknown	Datasets not generally publically available; likely several datasets available from federal agencies	Varies	Varies

Land Use/Land Cover and Change Datasets

The land cover and land cover change datasets evaluated for use in this project are summarized in Table A-3. Of these datasets, the NLCD 2006 dataset and change dataset (and associated NCLD impervious cover datasets) were selected as they are believe to provide the most recent, spatially-consistent, and extensive sample pool available. Of primary relevance, this dataset provides an assessment of impervious cover at a nationwide scale that is temporally consistent with available imagery and CBG attribute datasets. In addition, this dataset potentially allows evaluation of change in impervious cover associated with change from greenfield to urban land uses as well as change between densities of urban land uses and continuous estimates of change in imperviousness

A number of regional land use datasets have been identified throughout the country with varying attributes of resolution, number of land use classes, and data format. However, in general these data are not as widely available for public use. In addition, difference in land use coding and resolution complicates the use of these datasets.

Table A-3: Summary of Land Cover Datasets Considered for Analysis

Dataset/Extent	Details	Image Year	Source
NLCD 2001/Nationwide	Has 4 classes for urban land (H, M, and L intensity and developed OS)	2001	MRLC
NLCD 1992/2001 Change / Nationwide	Only describes one urban land category for changes	1992/2001	MRLC
NLCD 2006 / Nationwide	Describes 4 classes of urban land (H, M, and L intensity and developed OS)	2006	MRLC
NCDC 2001/2006 Change	Will describe change between 4 categories of urban land	2001/2006	MRLC
C-CAP/ coastal areas	Describes 4 classes of urban land (H, M, and L intensity and developed OS)	2006	NOAA
C-CAP change dataset / coastal areas	Describes change between 4 categories of urban land	2001/2006	NOAA
Local and regional land use and zoning maps	Details vary; generally shapefile polygons with region-specific zoning/land use codes (generally limited availability in unrestricted GIS format; commonly provided as pdf plots)		

NCLD 2006 land cover datasets were analyzed using zonal statistics features in the ArcGIS Spatial Analyst Extension and the stand-alone STARSPAN program (Rueda, C.A., Greenberg, J.A., and Ustin, S.L. StarSpan: A Tool for Fast Selective Pixel Extraction from Remotely Sensed Data. (2005). Center for Spatial Technologies and Remote Sensing (CSTARS), University of California at Davis, Davis, CA.)

Census Block Groups and Census Data

Census Block Groups (CBGs) are defined by political boundaries and population. CBGs generally contain between 600 and 3,000 people, with an optimum size of 1,500 people. CBGs never cross the boundaries of states, counties, or statistically equivalent entities, except for a CBG delineated by American Indian tribal authorities. In decennial census data tabulations, a CBG may be split for statistical purposes (Source: http://www.census.gov/).

For the purpose of this analysis, the CBG delineations compiled as part of the *Smart Location Index* project (Theobald et al., 2011, discussed below). Figure A-1 and Figure A-2 show examples of CBG delineations in the greater Portland (OR) area. Note that the size of CBGs varies greatly depending on residential density.

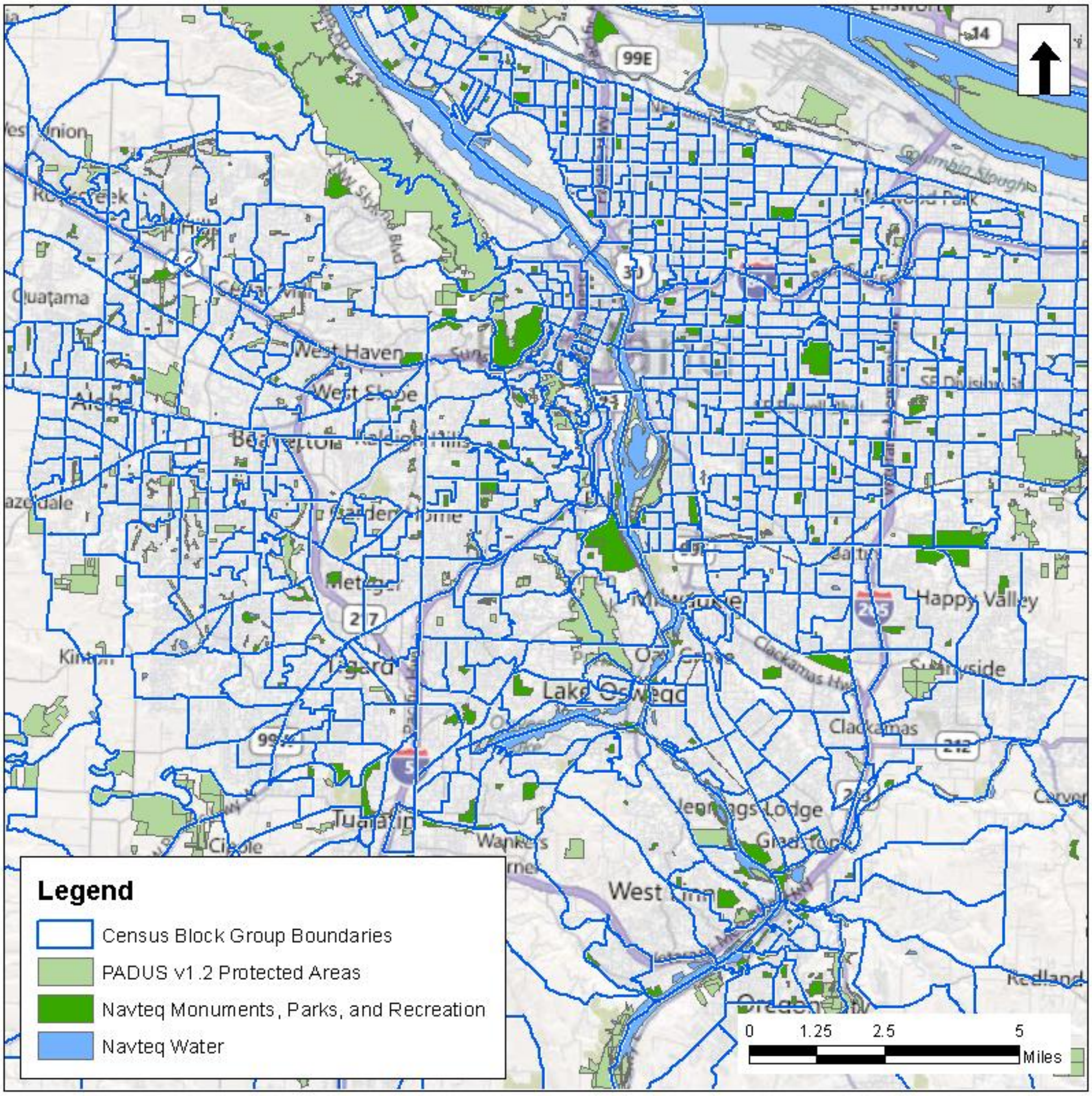


Figure A-1. Example CBGs and Protected Area Datasets, Portland, OR

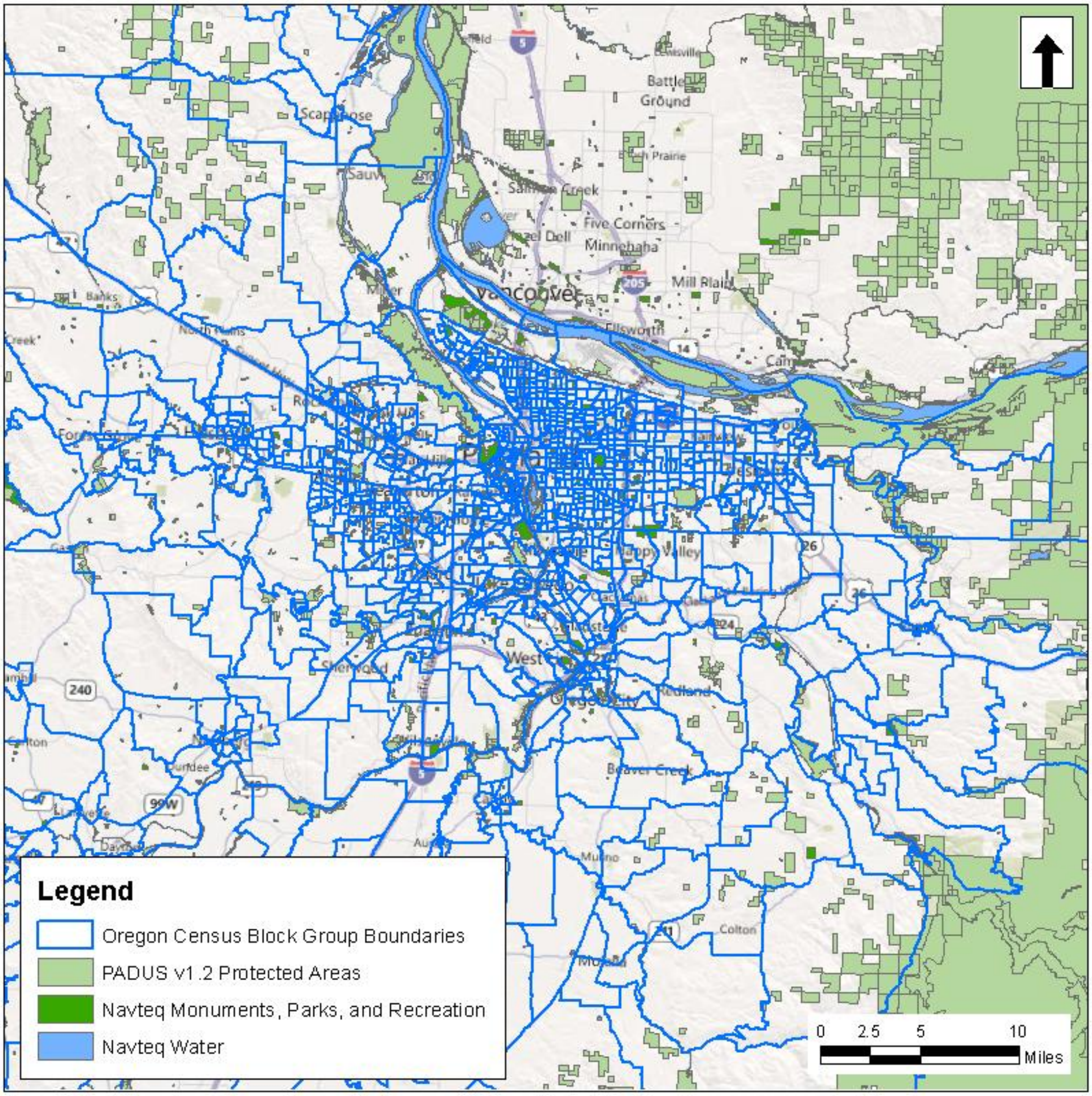


Figure A-2. Example CBGs and Protected Area Datasets, Portland, OR Vicinity

Various Political Boundaries

Various political boundaries, such as state boundaries and metropolitan statistical area (MSA) boundaries were obtained for this project from the US Census website. For example, MSA boundaries for the conterminous United States are shown in Figure A - 3.

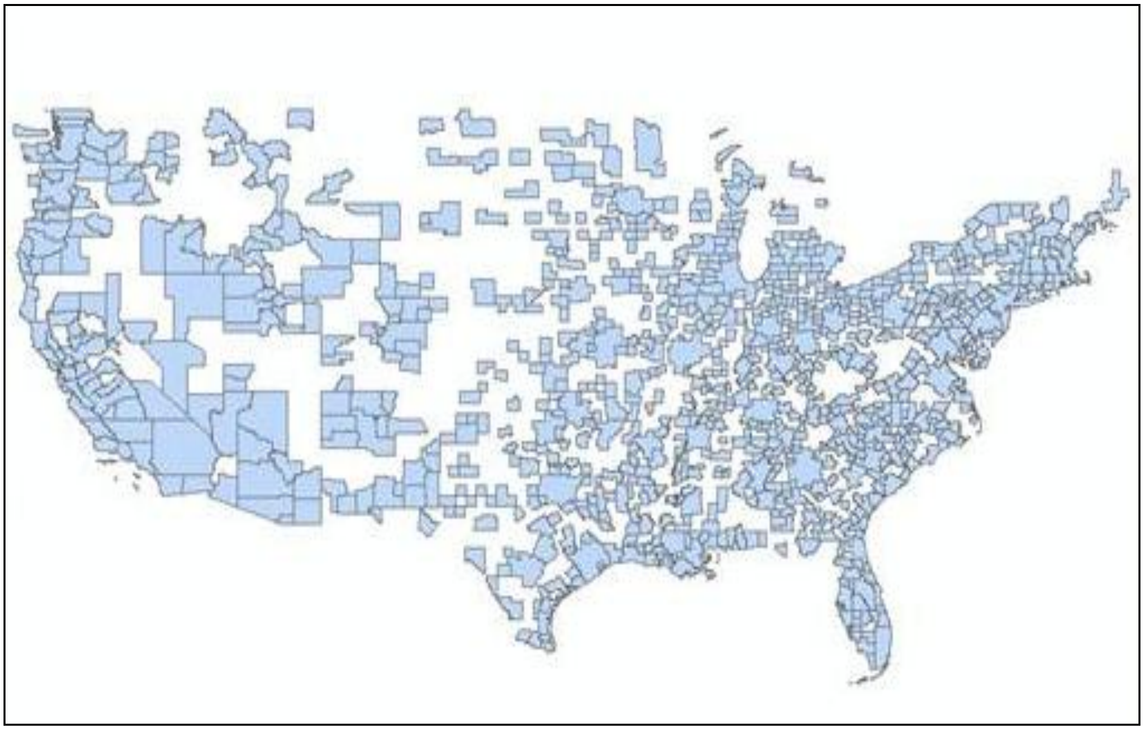


Figure A - 3: Metropolitan Statistical Areas (U.S. Census Bureau, 2000)

SLI Dataset

The study titled *A Smart Location Index to Evaluate Green Building Policies* (SLI study, Theobald, D.M., 2011) resulted in a nationwide dataset containing a various metrics impacting transportation efficiency or accessibility for each of the nation's CBGs. The study applies the 5D's of land use planning (density, land use diversity, urban design, destination accessibility, and distance to transit) to compute a composite index as an indicator vehicle miles traveled and other land use planning-related metrics. Based on our review of this study, approximately twenty factors and sub-factors were initially identified for potential use in the regression model (See Table A-4).

Table A-4: Potentially Relevant Accessibility Factors (Theobald et al., 2011)

FACTOR NAME	FACTOR DESCRIPTION
HU2009	Housing Units 2009
POP2009	Population 2009
Emp_Work	Total employment in 2009
R_WorkPop	Jobs-to-Population ratio
HU2009_ac	Housing Units per acre
Acres_priv	Acres of private land
D1Ap	Housing Units per Private Acre
D1Bp	Population per Private Acre
D1Cp	Jobs per Private Acre
D2a	Land Use Diversity

FACTOR NAME	FACTOR DESCRIPTION
D2b	Jobs to Pop ratio
D4a	Stations w/in 1/4 mile (major transit stations)
D4b	Stations w/in 1/2 mile (major transit stations)
D5ae	Destination Accessibility (employer perspective), gravity model
D5ar	Destination Accessibility (resident perspective), gravity model
D5be	Accessibility via transit (employer perspective)
D5br	Accessibility via transit (residential perspective)
SLIe	Smart Location Index (employer perspective)
SLIr	Smart Location Index (residential perspective)

An example plot of the 5Dar metric for the Portland vicinity is shown in Figure A - 4.

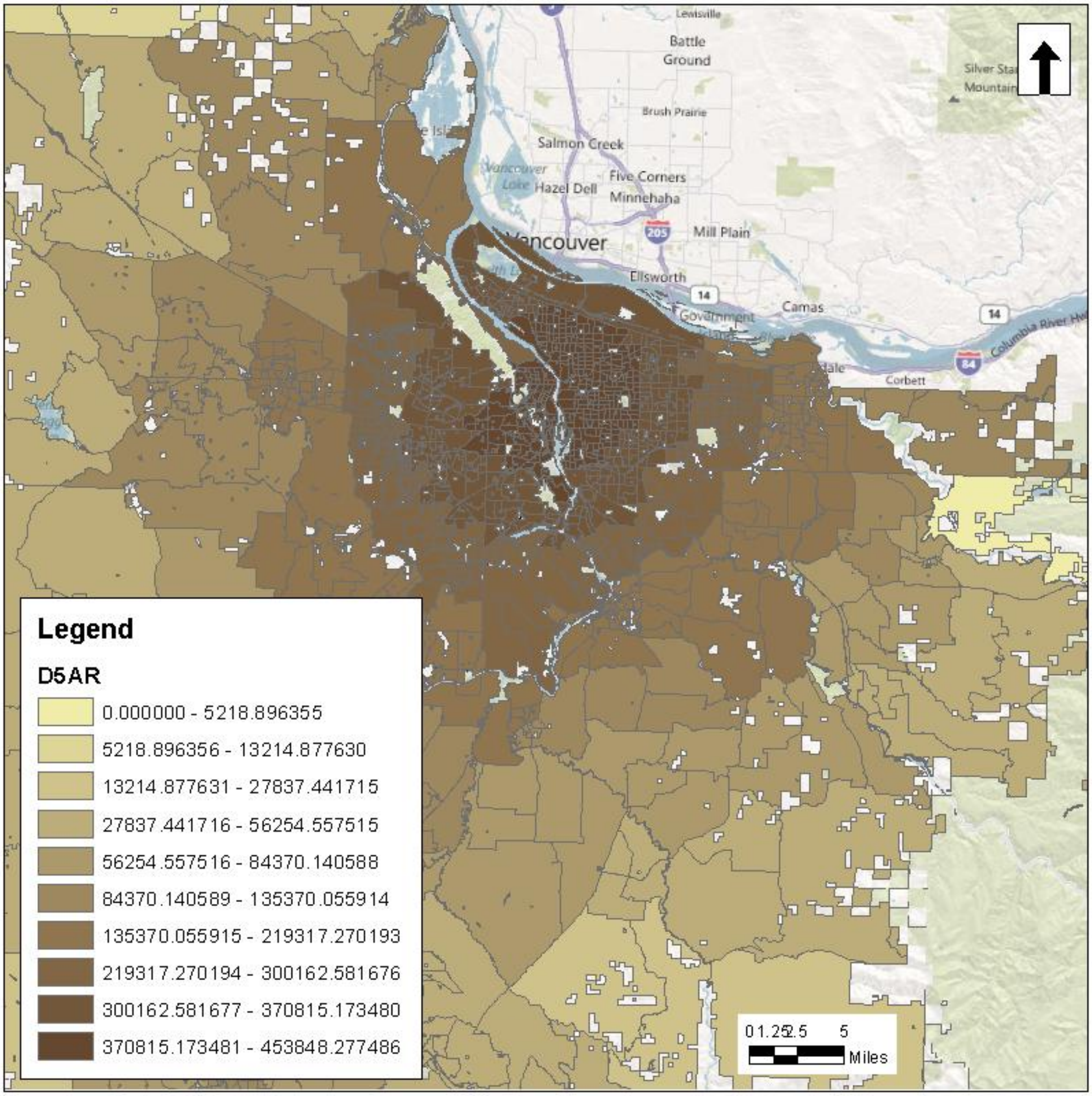


Figure A - 4: Spatial Distribution of the D5Ar Metric for Portland, OR

Local Employment Dynamics Dataset (LED)

The LED provides yearly snapshots of various employment statistics for each Census Block (one degree finer than CBGs). These statistics can be accessed through LED's "On The Map" interface or via ftp download of raw data files. Data are currently available from 2002 to 2008. This dataset describes employment, but does not describe commercial construction activity. For the purpose of this project, we downloaded and processed the LED dataset to yield estimates of jobs by sector for each supported CBG. Note, several states do not participate in the LED program.

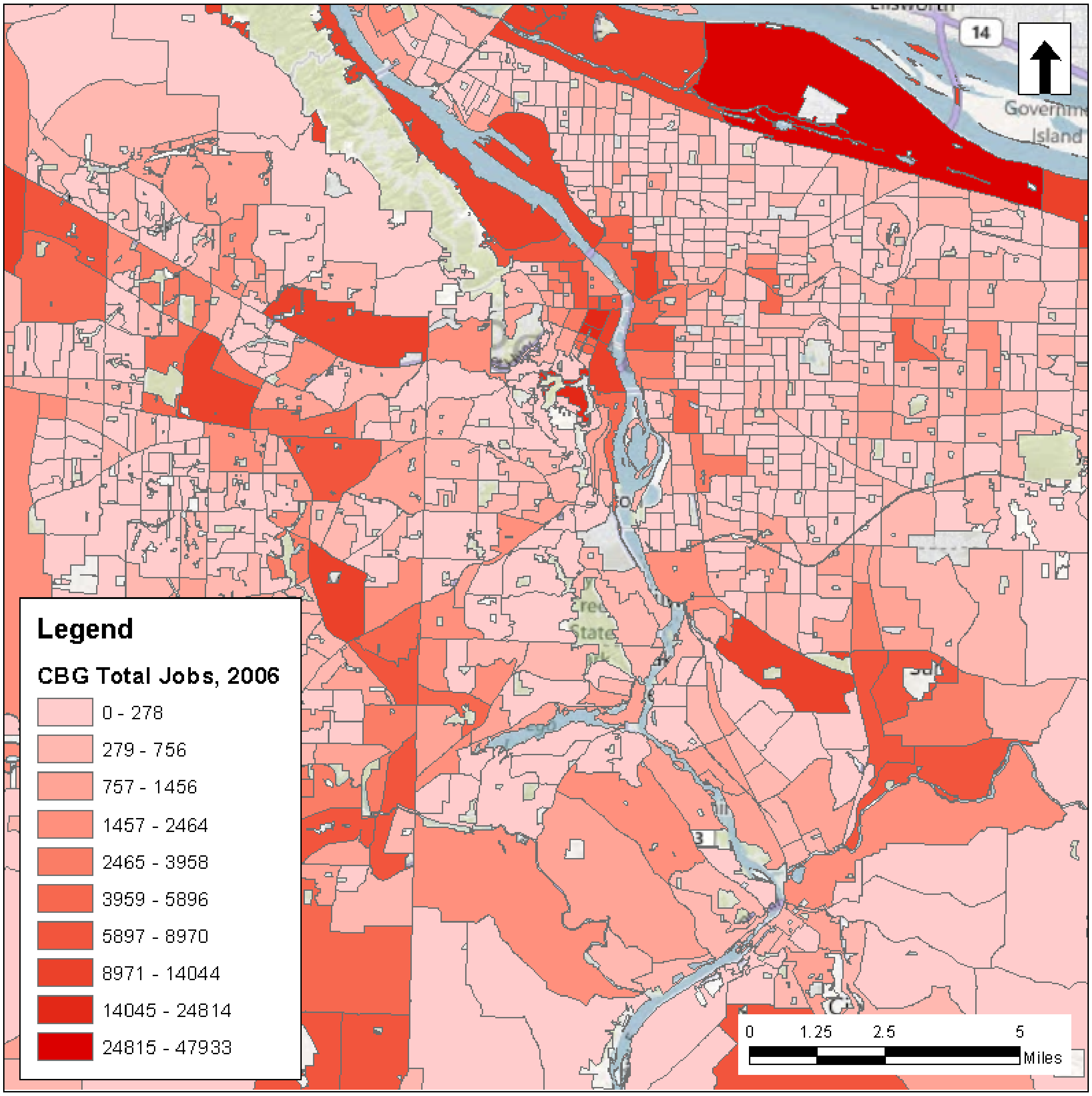


Figure A - 5: Example LED Employment Data by CBG, Portland, OR, 2006

Protected Areas Datasets

Areas that are protected from development were derived from various sources, including:

- Protected Areas Database – US (PADUS) v1.2 (http://gapanalysis.usgs.gov/data/padus-data/),

- Navteq land use (Navteq, 2011) – Local, state, and regional parks; cemeteries, and similar uses.
- Navteq water features (Navteq, 2011) – Rivers, lakes, bays, and other water features.
- NLCD 2006 (MRLC, 2011) - water land cover

These datasets were integrated to yield a nationwide dataset of regions that are considered to be protected and unprotected. Protected areas from the PADUS and Navteq datasets are shown in Figure A-1 and Figure A-2 for the greater Portland (OR) area. Protected areas were removed to make CBG statistics more representative of the portions of the CBG that are developable. Specific descriptions of inputs, assumptions, and quality control checks are shown in Table A-5

Table A-5: Unprotected Areas Analysis Inputs, Assumptions, and Quality Controls

Definitions:	
Unprotected	Unprotected areas are defined as all areas within a CBG that are not within one of more of the following categories: PADUS protected areas, NAVTEQ parks, NAVTEQ water polygons, NLCD water land cover
Agricultural	Agricultural land cover is defined as "cultivated crops" and "pasture/hay"
Wilderness	Wilderness land cover is defined as all other undeveloped land covers excluding those identified in the definition of "agricultural"
Developed	Developed land cover is defined as "developed open space", "developed low intensity", "developed medium intensity", and "developed high intensity"
Undeveloped	All land covers that are not included in the definition of "developed"
Input Datasets:	
CBGs	Based on SLI_2009 CBG dataset provided by USEPA for Geosyntec's use
PADUS	Originator: US Geological Survey (USGS) Gap Analysis Program (GAP) Title: Protected Areas Database of the United States (PADUS) version 1.2 Publication Date: 2-22-2011 Edition: 1.2 Online linkage: <http://gapanalysis.usgs.gov/PADUS>
NAVTEQ	Navteq Parks and Water Polygons provided by USEPA for Geosyntec's use. The following FEAT_TYP Values were queried for use: ANIMAL PARK; BEACH; CEMETERY; PARK (CITY/COUNTY); PARK (STATE); PARK IN WATER; PARK/MONUMENT (NATIONAL)
NLCD 2006	Originator: U.S. Geological Survey Publication_Date: 20110216 Title: NLCD 2001/2006 From - To Change Index (Supplementary Raster Layer) Edition: 1.0
Summary of Analysis Steps/Methods:	
Union 1	Union selected NAVTEQ parks polygons with NAVTEQ water polygons
Union 2	(a) Union 1 with PADUS protected areas polygons. (b) Selected features from PADUS database listed as “Designated – Legally or administratively decreed” (Field = [Status]). (c) Tentatively reviewed names of places (Field = [Primary Local Name]} and

Table A-5: Unprotected Areas Analysis Inputs, Assumptions, and Quality Controls

	owner designation (Field = [Owner Type]). Upon further review, many tribal lands and military bases fall into this category and were not excluded.[1] This introduces systematic bias in calculation of true unprotected area for CBGs with military or tribal ownership. The report describes reasonableness screening that was conducted to address clear cases of this bias.
Union 3	Union 2 with CBG polygons
Query1	Query areas of Union 3 that are not overlain by PADUS or NAVTEQ protected areas to yield unprotected areas polygon
Spatial Analysis 1	Parse by state and loop through spatial analysis of NLCD change indices for each unprotected area polygon generated by Query 1; produce tabular histogram of pixel count by NLCD class
Query 2	Query histogram produced from Spatial Analysis 1 to produce final summation of unprotected area land cover acreages by CBG. Land cover groupings by parsing "land cover change index" into "from" and "to" components. Acreages computed by multiplying pixel count by fixed area conversion factor.
Summary of Quality Control Procedures and Checks:	
Input Dataset Check	Check for complete coverage; project into same coordinate system as NLCD datasets; no warrantee on quality of input datasets obtained from publishing organizations
Spatial Union Checks	Review results of each union by individual spot checks and aggregated statistical checks
Spatial Analysis Checks	Review results by individual spot checks and aggregated statistical checks at CBG, state, and national scale.
Final Dataset Checks	Individual spot checks, manual verification of land cover class groupings and summations, check of queries, check of reasonableness of values based on state and nationwide aggregated statistics, comparison of unprotected acreages to 2009 SLI "private acreage"
Post-hoc reasonableness checks	After integration of the protected area datasets with housing and employment data, steps were taken to address the clearest examples of inaccuracies that resulted from the above limitations introduced by the consideration of tribal and military ownership as protected lands. This is documented in the report.
Notes:	
1	Shapefiles of unprotected areas include minor areas that are zoned as NLCD water are not already included in PADUS or NAVTEQ layers; these were considered to be protected and the areas are not included in this database
2	PADUS and NAVTEQ protected areas are based on the latest versions of these datasets and do not change between 2001 and 2006.
3	Acreage of unprotected area may change slightly from 2001 to 2006 as a result of changes in the acreage of NLCD water land cover not aready included in PADUS or NAVTEQ layers.

[1] In retrospect, all tribal lands and military bases should *not* have been included as protected land type, due to the fact that people live and work on these lands.

Table A-5: Unprotected Areas Analysis Inputs, Assumptions, and Quality Controls

4	In somewhat rare cases (approximately 0.2% of CBGs), development exists within areas that are considered to be protected in the PADUS database. This is believed to potentially represent mischaracterization of the area as protected as a result of military or tribal land or the presence of more complex land use overlays that would prevent future development. Steps were taken to address the clearest examples of inaccuracies that resulted from the above limitations. This is documented in the report.
5	Some CBGs have zero unprotected area. In general, these CBGs are anomalously small CBGs that are too small to contain more than half of any NLCD pixel. In somewhat rare cases mentioned above, entire CBGs containing development are considered to be protected in the PADUS database.
6	Coverage includes conterminous US based on current extent of NLCD 2006 dataset; AK and HI are not supported by this analysis.

Appendix B

Exhibits Supporting Preliminary Data Analysis

Data Quality and Reliability Checks

The following exhibits were generated as examples of data quality and reliability inspections that were conducted. A summary of observation are provided below.

Exhibit B-1 Comparison of NLCD to City of Portland High Resolution Land Cover

> This exhibit illustrates the resolution of the NLCD impervious cover dataset and provides the results of a comparison between the NLCD dataset and high resolution impervious cover dataset in the Portland (OR) metro area.
>
> While there is some error associated with the NLCD dataset in comparison to higher resolution dataset, the relative fit of the data is strong and there does not appear to be substantial bias.

Exhibit B-2 Suburban Infill Signature, SW 209th and Farmington Road, Oregon

> This exhibit was used as a visual inspection to evaluate the reliability of NCLD impervious cover change estimates (2001-2006) versus inspection of aerial photography taken circa 2001 and 2006.
>
> For suburban infill type locations and a relatively sizable project, the NCLD dataset appears to detect the change in impervious cover relatively reliably.

Exhibit B-3 Urban Fringe Signature, Clackamas County, Oregon

> This exhibit was used as a visual inspection to evaluate the reliability of NCLD impervious cover change estimates (2001-2006) versus inspection of aerial photography taken circa 2001 and 2006.
>
> For urban fringe type development and a relatively sizable project, the NCLD dataset appears to detect the change in impervious cover relatively reliably.

Exhibit B-4 Urban Infill Signature, SE 122nd and Holgate, Portland, Oregon

This exhibit was used as a visual inspection to evaluate the reliability of NCLD impervious cover change estimates (2001-2006) versus inspection of aerial photography taken circa 2001 and 2006.

Based on this inspection, the NLCD does not appear to be reliable for detecting small distributed densification projects in CBGs such as this. The NLCD showed no change in impervious cover, while inspection of aerial photography indicates that densification has occurred (subdivision of lots, conversion of detached to attached dwellings). These changes are called out on the exhibit. Similar trends are observed in similar CBGs. Because the high resolution impervious cover dataset is not available for other points in time, a quantitative assessment of the amount of impervious change that was not detected by NLCD could not be conducted. In general, it appears that where changes in development intensity were not sufficient in scale or magnitude to trigger reclassification of NCLD development intensity (i.e., L to M, M to H), impervious change was not detected. Tree cover did not appear to be a significant factor in undetected impervious surface growth.

Exhibit B-5 Ultra-Urban Infill Signature, Pearl District, Portland, Oregon

This exhibit was used as a visual inspection to evaluate the reliability of NCLD impervious cover change estimates (2001-2006) versus inspection of aerial photography taken circa 2001 and 2006.

While no change is shown in the NLCD dataset, this appears to be a relatively reliable result. In some parts of inner city areas that are highly imperviousness, it appears that development does not necessarily result in an increase in imperviousness.

Scatter Plot Matrix and Correlation Analysis

Scatterplot matrices were developed to quickly visualize various data combinations and evaluate whether potential relationships existed between block group variables. Non-parametric correlation coefficients (Spearman's rhos) were also produced to identify whether any monotonic relationships existed between variables. Five different filters were applied to the dataset to focus the analysis on particular block group characteristics. Results of correlation analyses and SPLOMs are shown in the following exhibits.

Exhibit B-6: Data Dictionary of Correlation and SPLOM Parameters Used in Preliminary Analysis

Exhibit B-7**:** Filter 1 - Random subset of all data (1/3rd of data points). This data filter was simply applied to reduce the number of data points to a more manageable number for analysis while preserving the general characteristics of the entire data set.

Exhibit B-8**:** Filter2 - Significant development/redevelopment. This data filter represents the block groups that experienced the highest changes in development from 2001 to 2006. This filter included CBGs meeting any of the following characteristics:

- Any land cover change
- Housing unit growth greater than the 50th percentile growth of all CBGs
- Total employment growth greater than the 50th percentile growth of all CBGs

Exhibit B-9**:** Filter 3 - Dominant Residential Change. This data set included CBGs from Filter 2 where housing unit growth was in the top quartile and employment growth was in the bottom quartile.

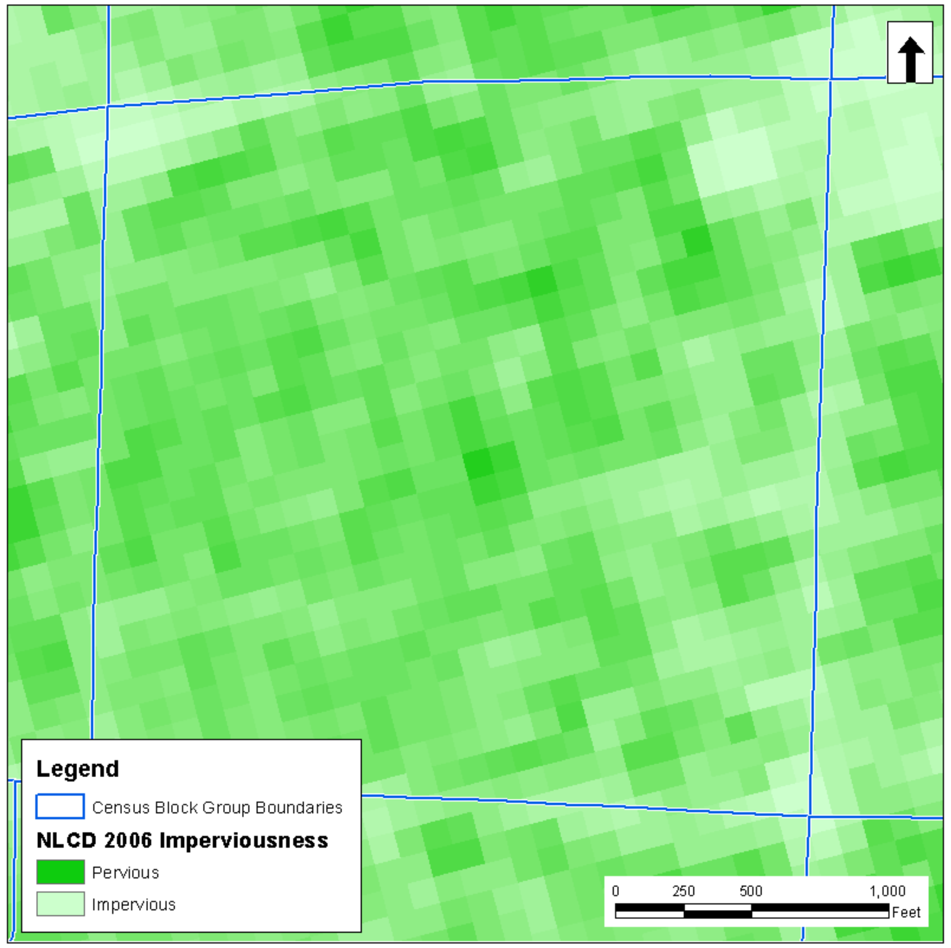
Exhibit B-10**:** Filter 4 - Dominant Employment Change. This data set included CBGs from Filter 2 where employment growth was in the top quartile and housing unit growth was in the bottom quartile.

Exhibit B-11**:** Filter 5 - Residential Dominated CBG in 2006. This data set includes block groups that were primarily residential in 2006, defined by having less than the 10th percentile of total employees (all CBGs have housing units by definition).

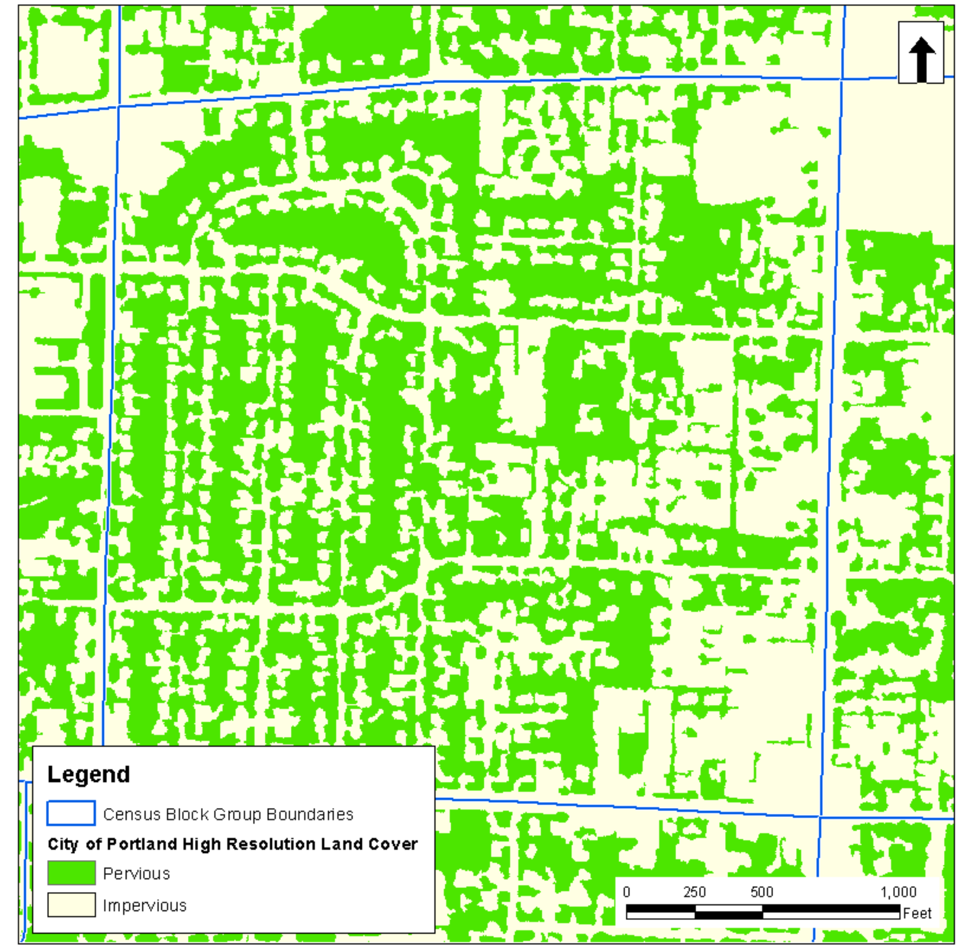
Exhibit B-12: Evaluation of Growth Management Policy (SGMRNK) as Possible Predictive or Stratification Variable (includes discussion)

Exhibit B-1
Comparison of NLCD to City of Portland High Resolution Land Cover

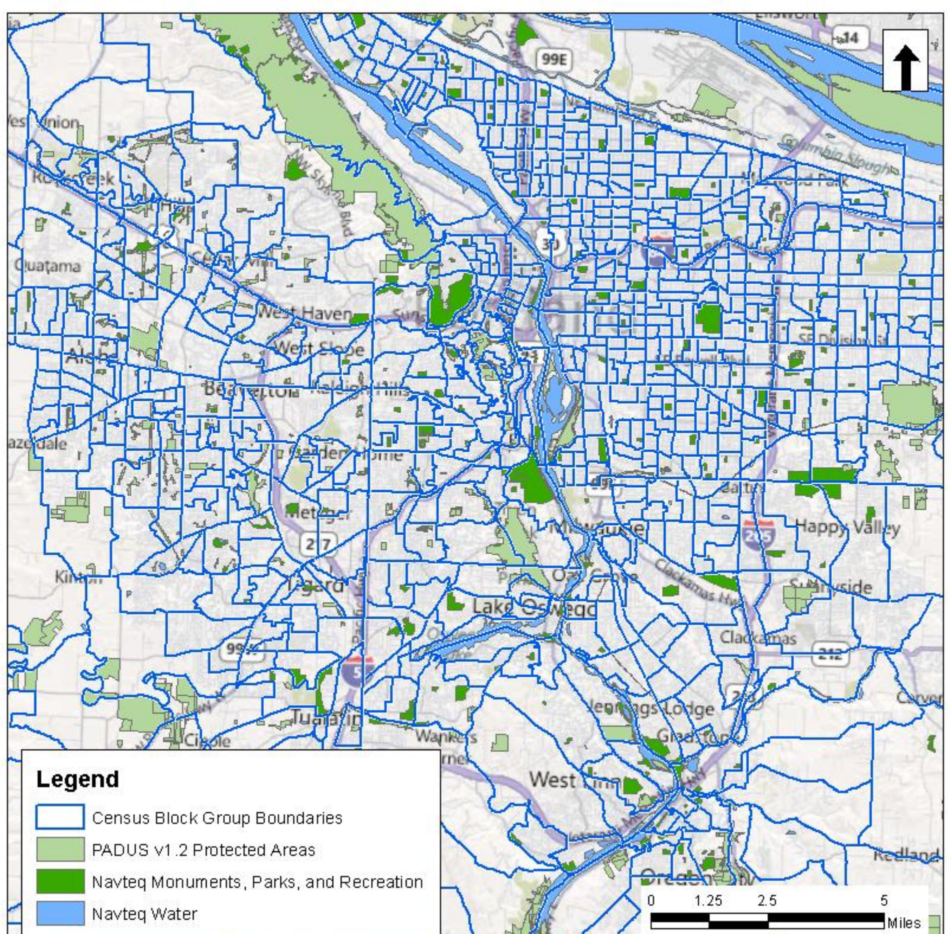
NLCD 2006 Impervious Cover (30 m)



2007 Portland High Resolution Land Cover Dataset (1 m)



Portland Area CBGs



Comparison of 2006 NLCD to 2007 HRLC for Portland Area CBGs

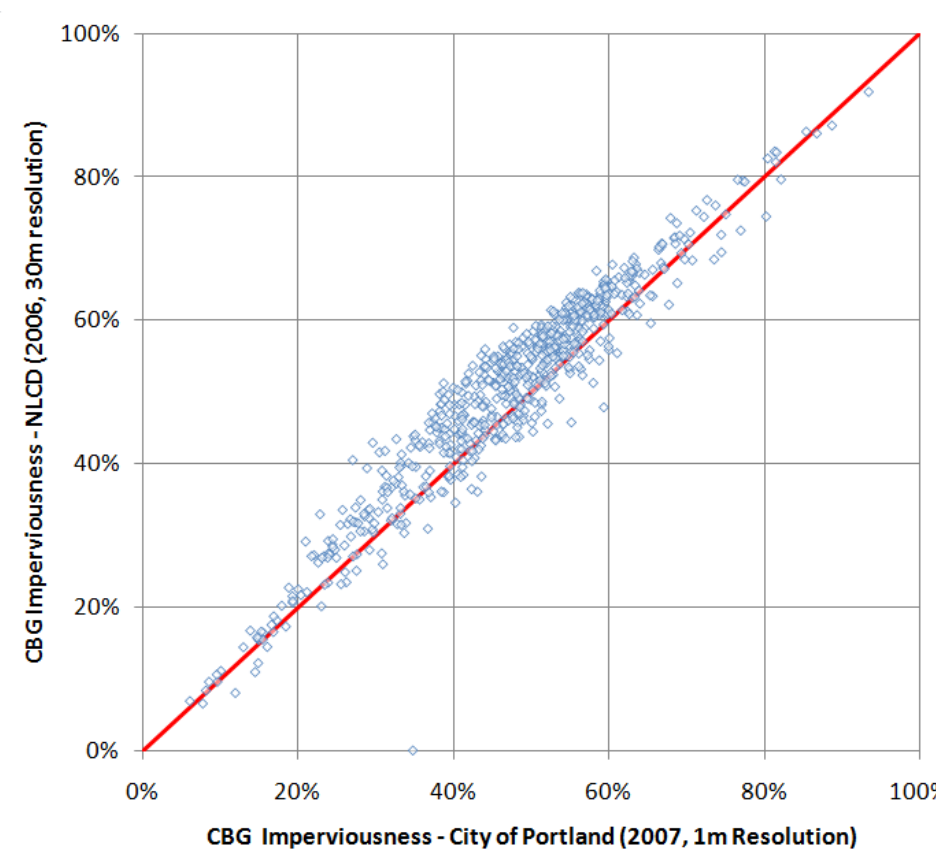
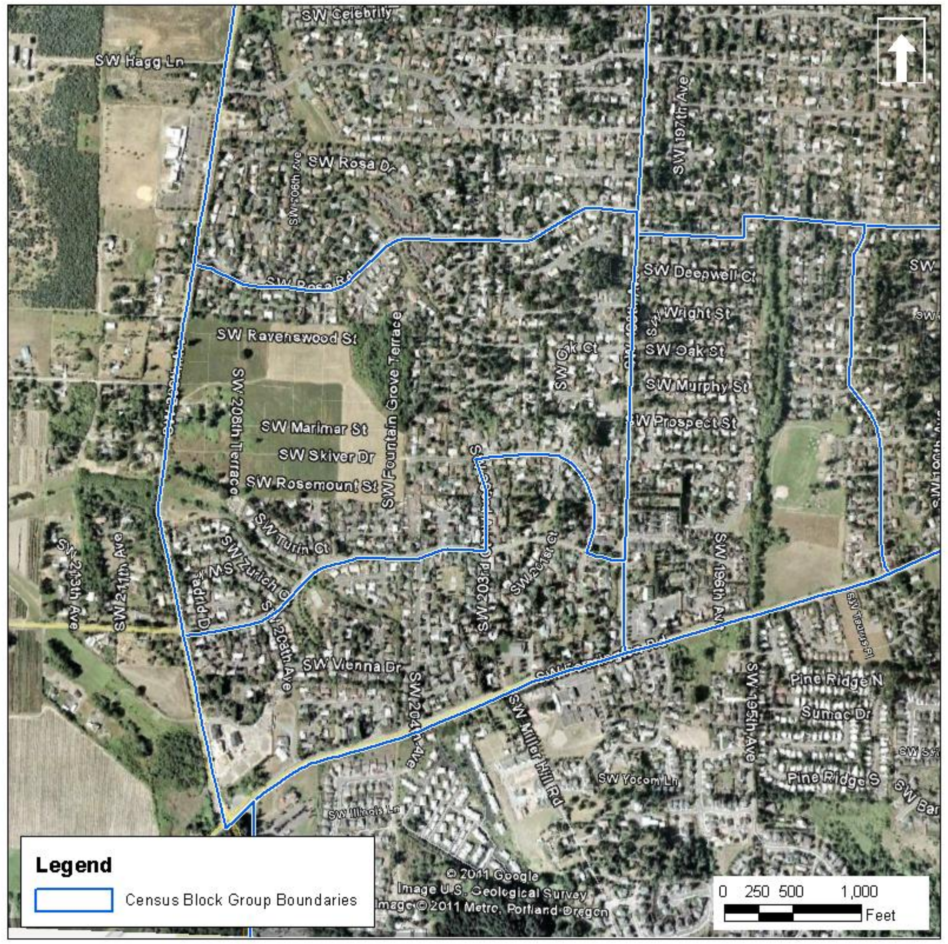


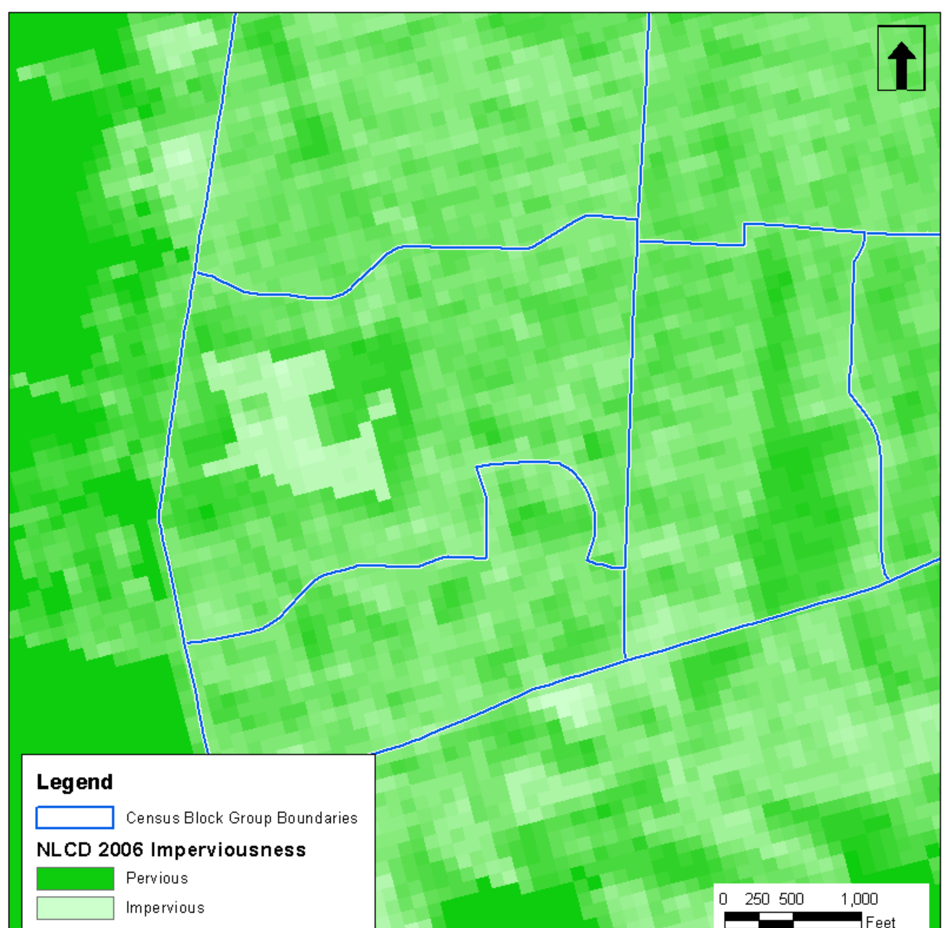
Exhibit B-2
Suburban Infill Signature
SW 209th and Farmington Road, Oregon

2001 Aerial Photo



2006 Aerial Photo

NLCD 2006
Impervious Cover



NLCD 2001-2006
Impervious
Change

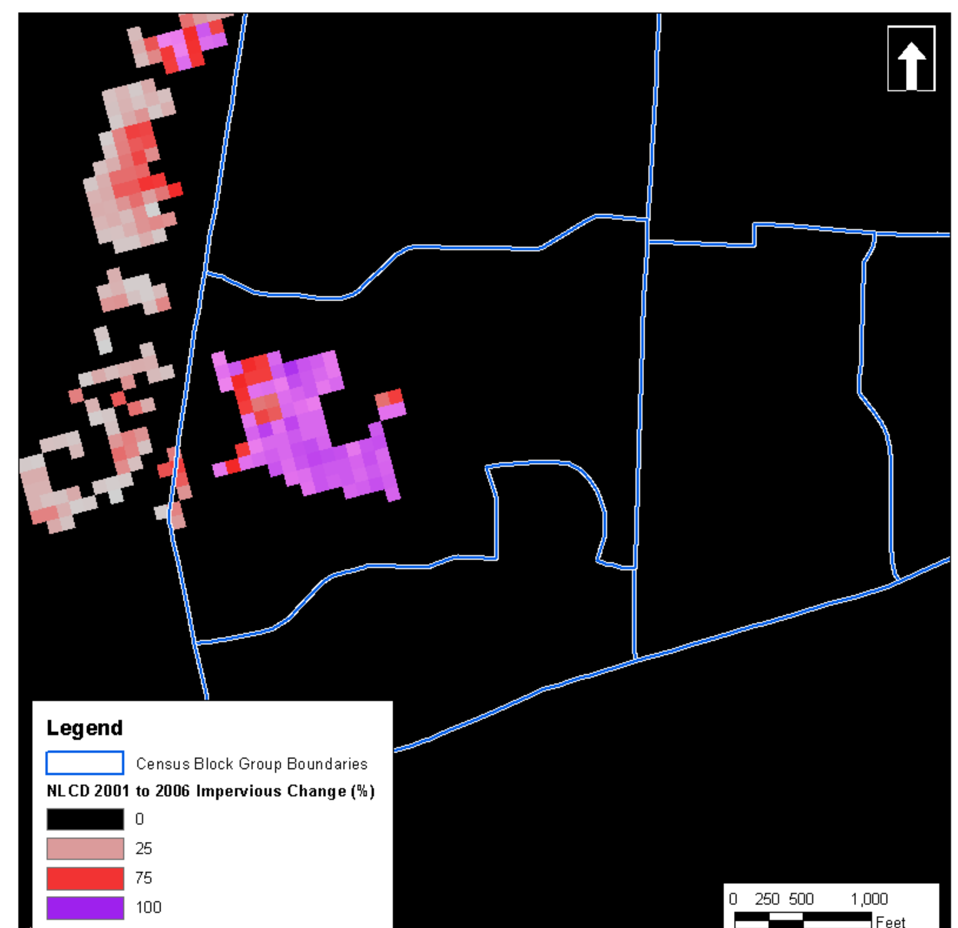
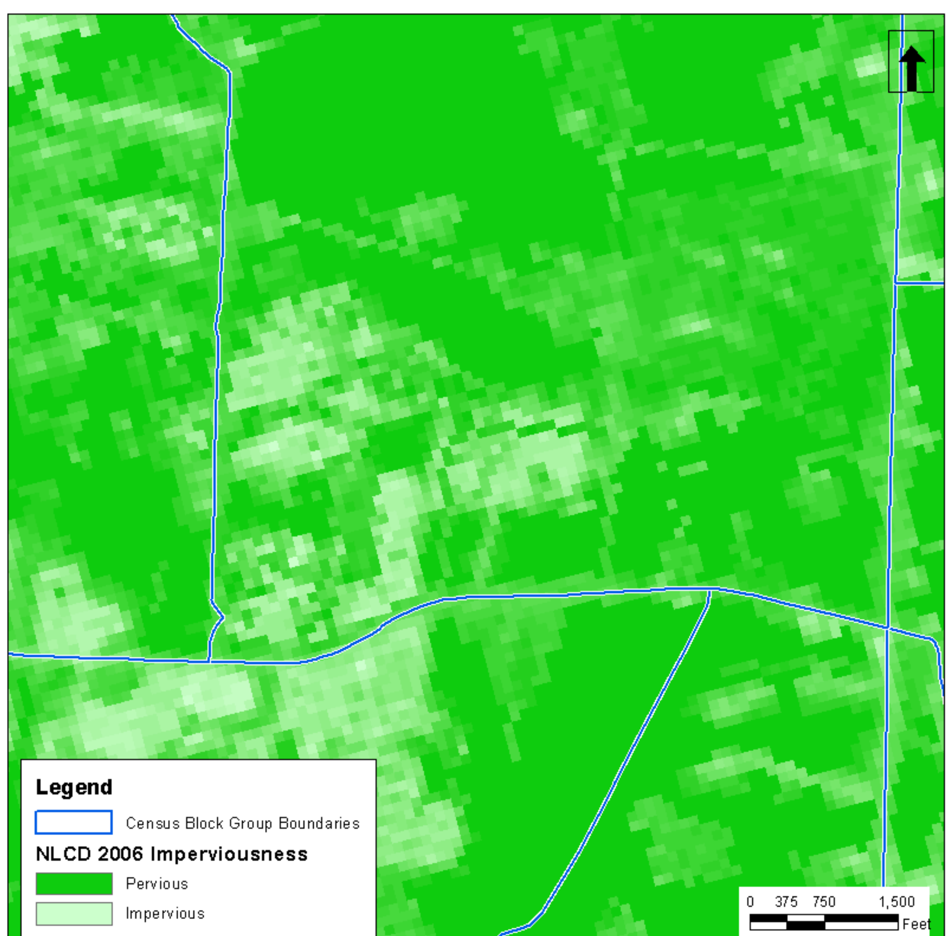


Exhibit B-3
Urban Fringe Signature
Clackamas County, Oregon

2001 Aerial Photo

2006 Aerial Photo

NLCD 2006
Impervious Cover



NLCD 2001-2006
Impervious
Change

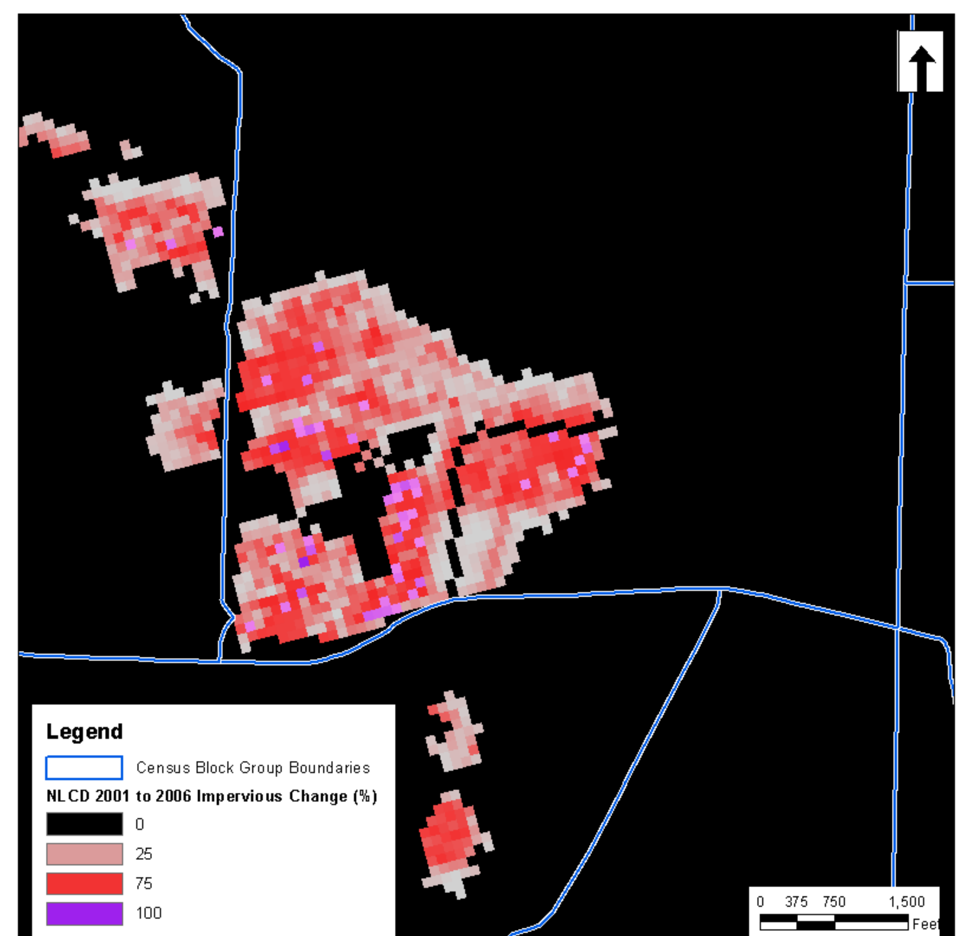
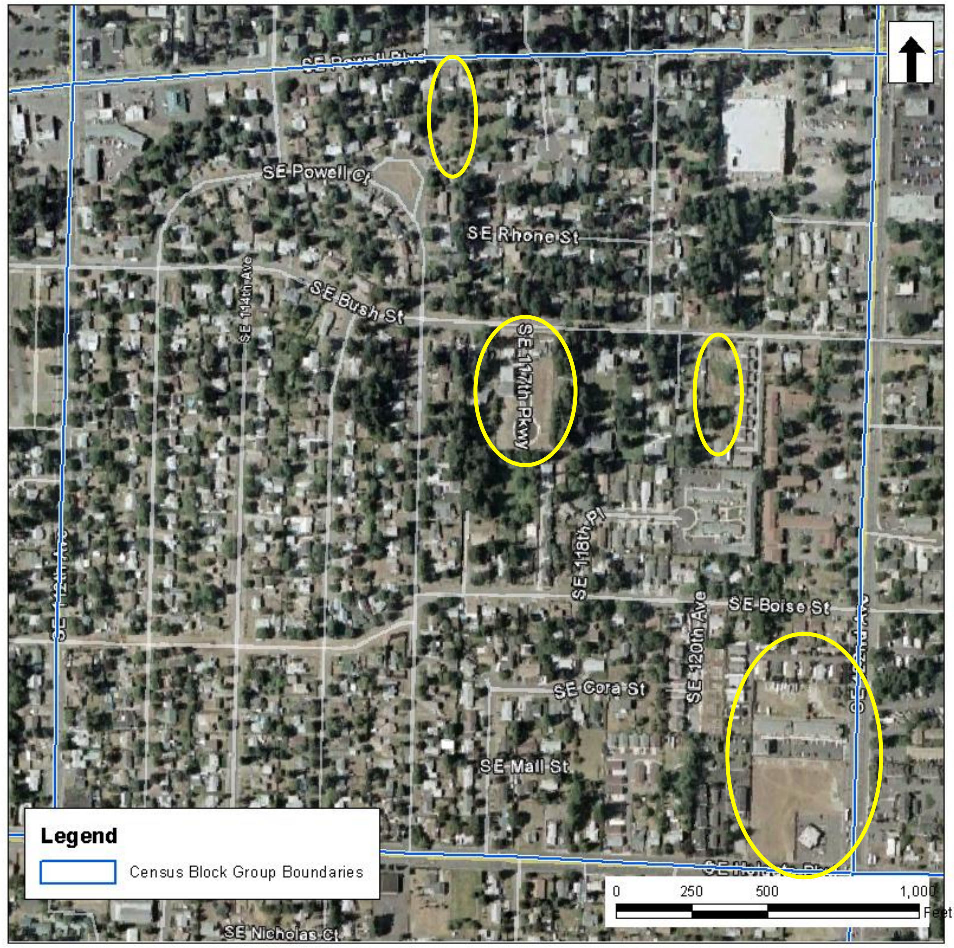
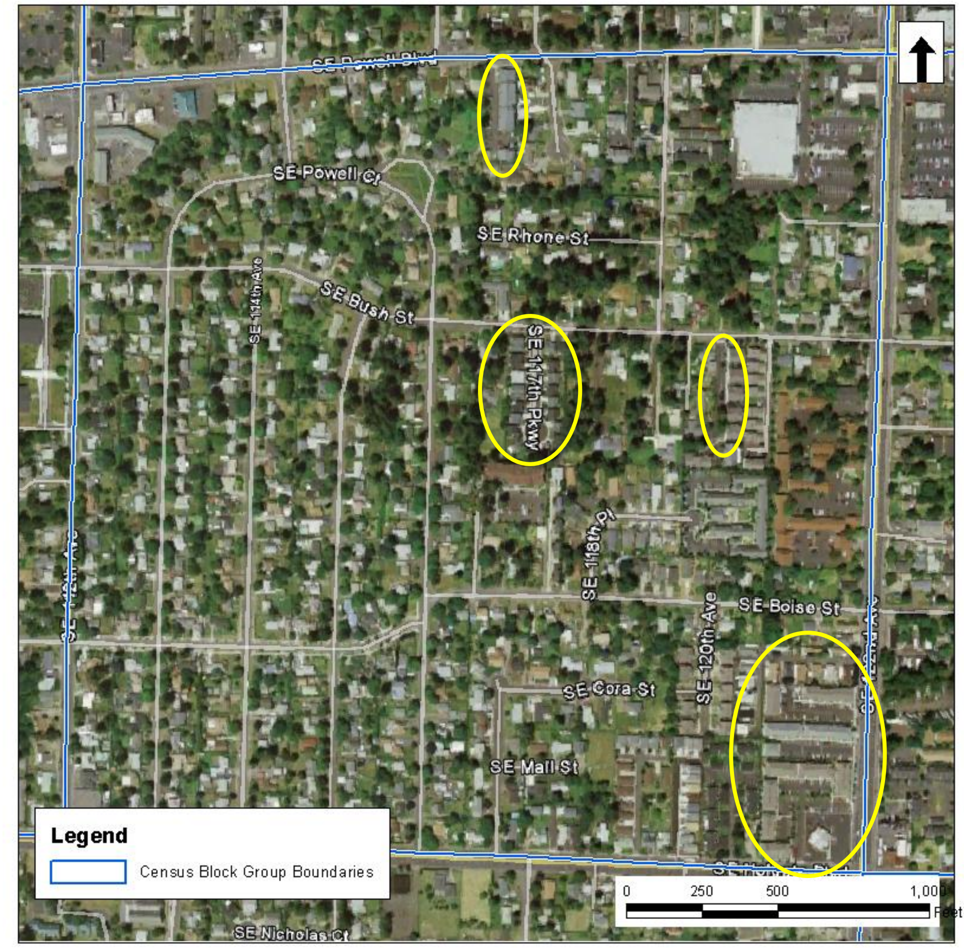


Exhibit B-4
Urban Infill Signature
SE 122nd and Holgate, Portland, Oregon

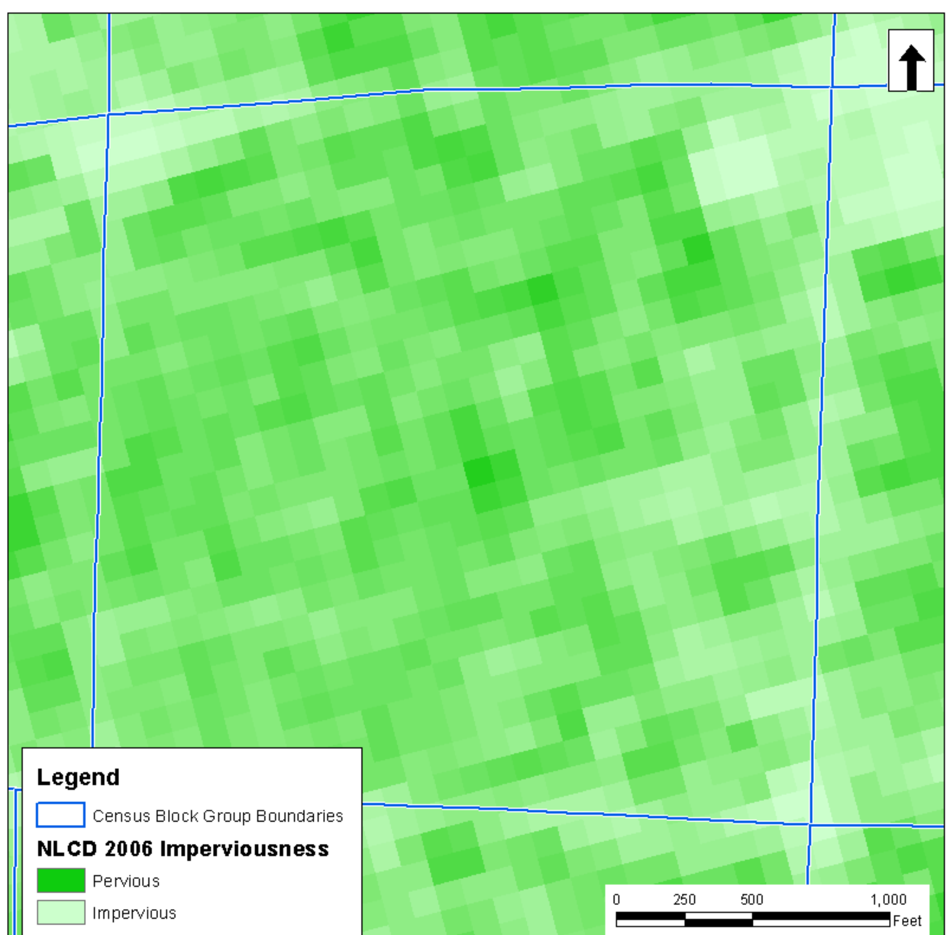
2001 Aerial Photo
Circles indicate areas where change appears to have occurred.

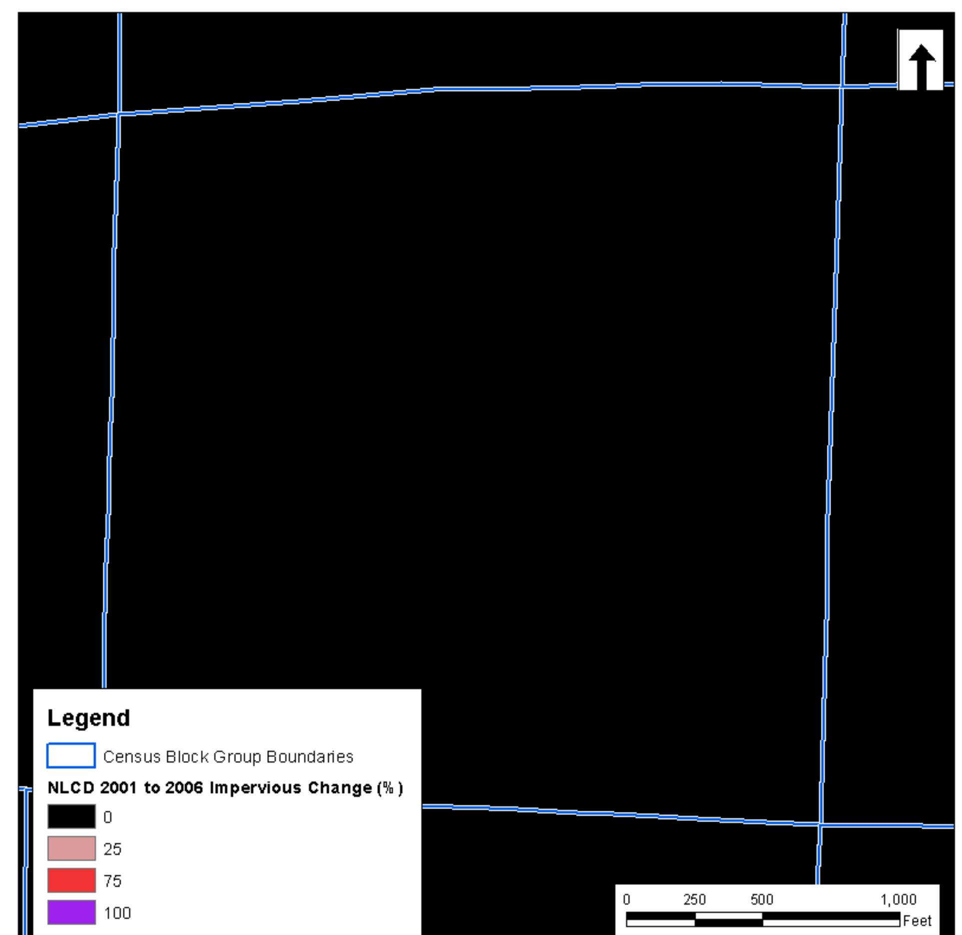




2006 Aerial Photo
Circles indicate areas where change appears to have occurred)

NLCD 2006 Impervious Cover

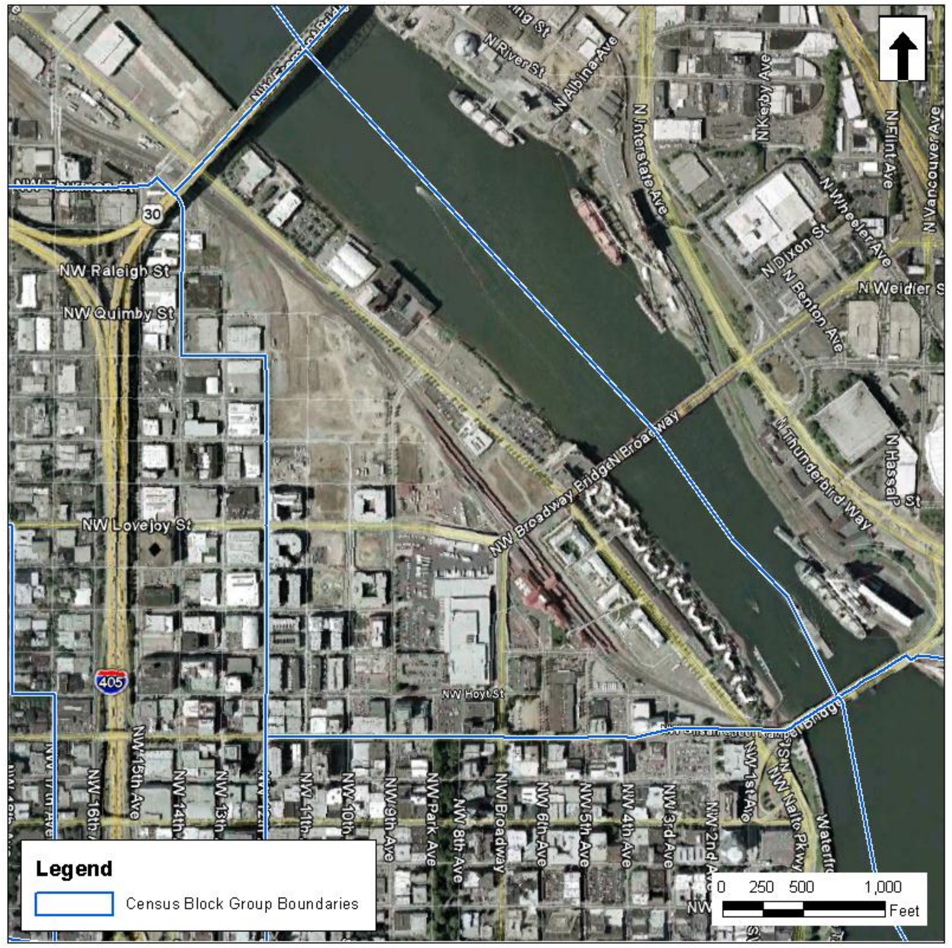




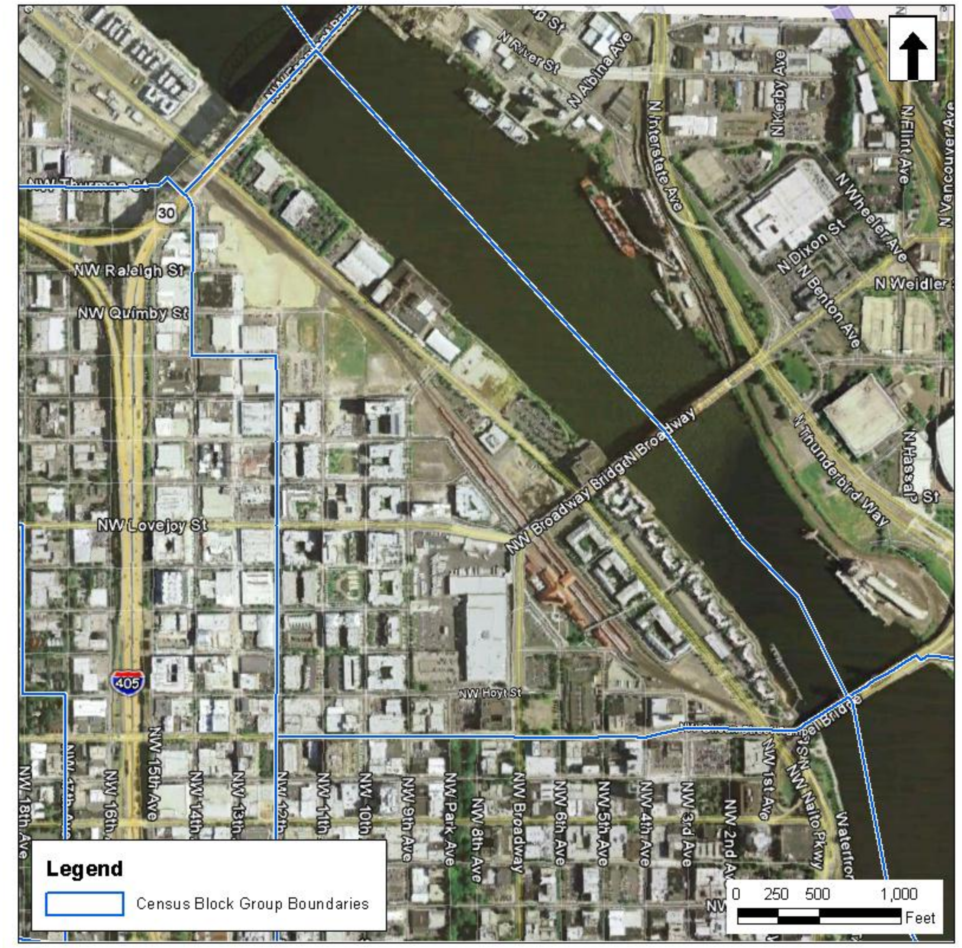
NLCD 2001-2006 Impervious Change

Exhibit B-5
Ultra-Urban Infill Signature
Pearl District, Portland, Oregon

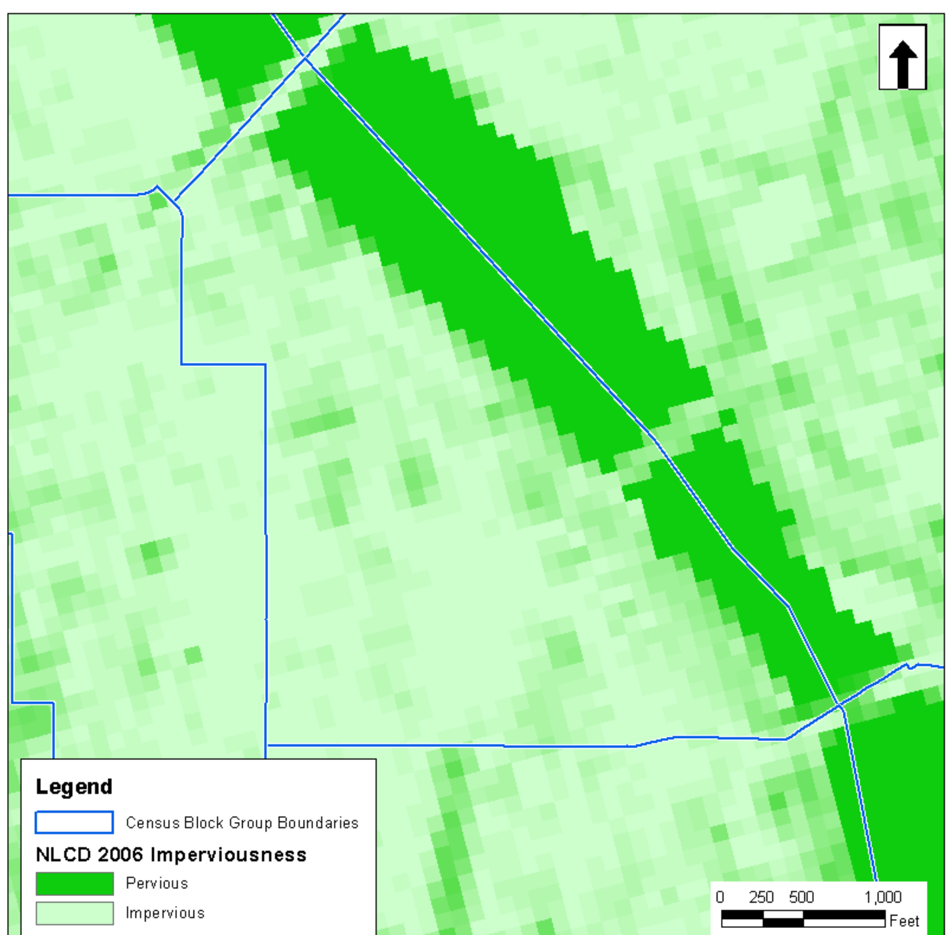
2001 Aerial Photo



2006 Aerial Photo



NLCD 2006 Impervious Cover



NLCD 2001-2006 Impervious Change

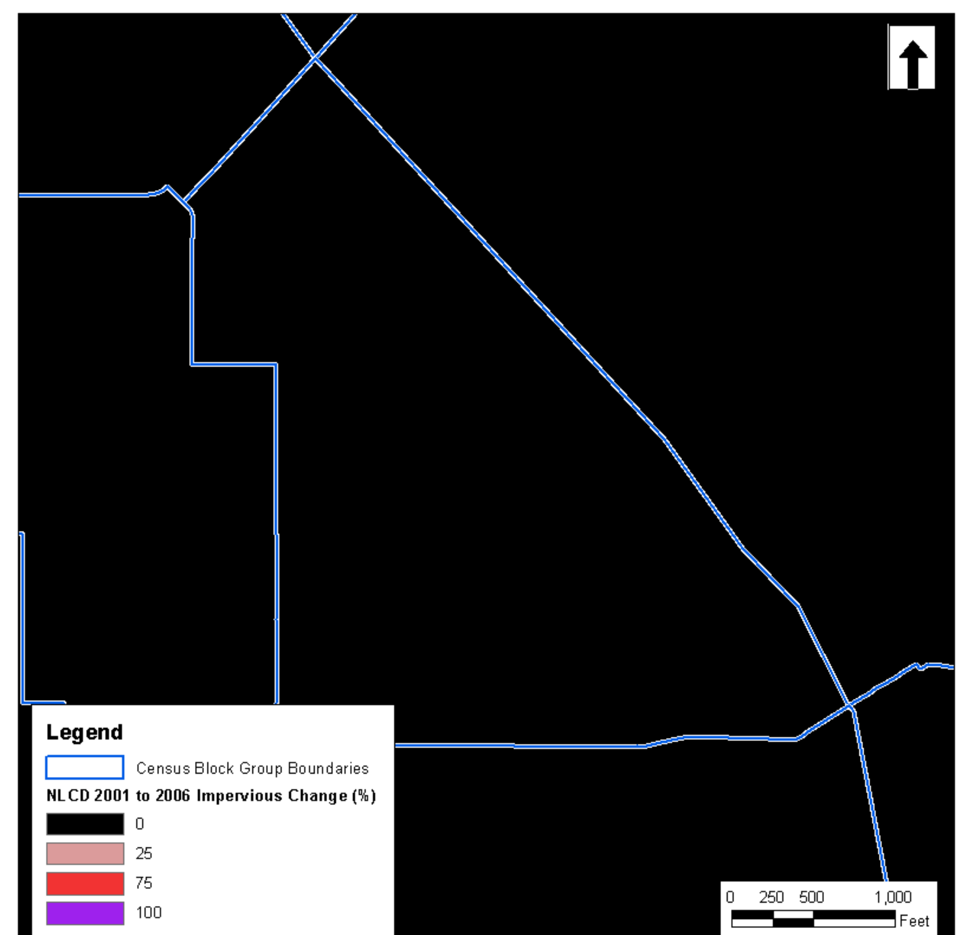


Exhibit B-6: Data Dictionary of Correlation and SPLOM Parameters Used in Preliminary Analysis

Parameter ID	Description	Units	Source
IMP_2006_AVG	Average Imperviousness of the CBG in 2006	%	NCLD, SLI
CHGIMP_AC	Change in impervious cover in CBG from 2001 to 2006	ac	NCLD, SLI
DIMP_DHU	Change in impervious area per change in housing units (2001-2006)	ac/hu	NLCD, SLI, HUD
DIMP_DE	Change in impervious area per change in employees (2001-2006)	ac/emp	NLCD, SLI, LEHD
CHG_EMP	Change in employees (est) (2001-2006)	emp	LEHD
CHG_HU	Change in housing units (est) (2001-2006)	hu	LEHD
_06I_06HU	Total impervious area normalized to number of housing units in 2006	ac/hu	NLCD, SLI, HUD
_06I_06E	Total impervious area normalized to number of employees in 2006	ac/emp	NLCD, SLI, LEHD
SLIR	Smart Location Index, Residential Perspective	-	SLI
SLIE	Smart Location Index, Employer Perspective	-	SLI
D1AP	Housing unit density, 2009, private area	hu/ac	SLI
D1BP	Population density, 2009, private area	pop/ac	SLI
D1CP	Employment density, 2009, private area	emp/ac	SLI
D5AR	Destination accessibility, residential perspective, gravity model	jobs	SLI
TLEIE_NEW	Transportation Location Efficiency Index, Employer Perspective	-	SLI
TLEIR_NEW	Transportation Location Efficiency Index, Residential Perspective	-	SLI
US_D5AE_S1	Destination accessibility, employer perspective, gravity model, US normalized	jobs	SLI
DEV_LC_CHG	Land cover change acreage from undeveloped to developed land cover types (2001-2006)	ac	NLCD, SLI
GF_LC_CHG	Land cover change acreage characteristic of greenfield conversion (2001-2006)	ac	NLCD, SLI
IN_LC_CHG	Land cover change acreage characteristic of infill development/densification	ac	NLCD, SLI
SGMRNK	Ranking of strength of growth management policy by state (0, 10, 15, 20)	integer	*Getting Back on Track* (Bhatt et al., 2009)

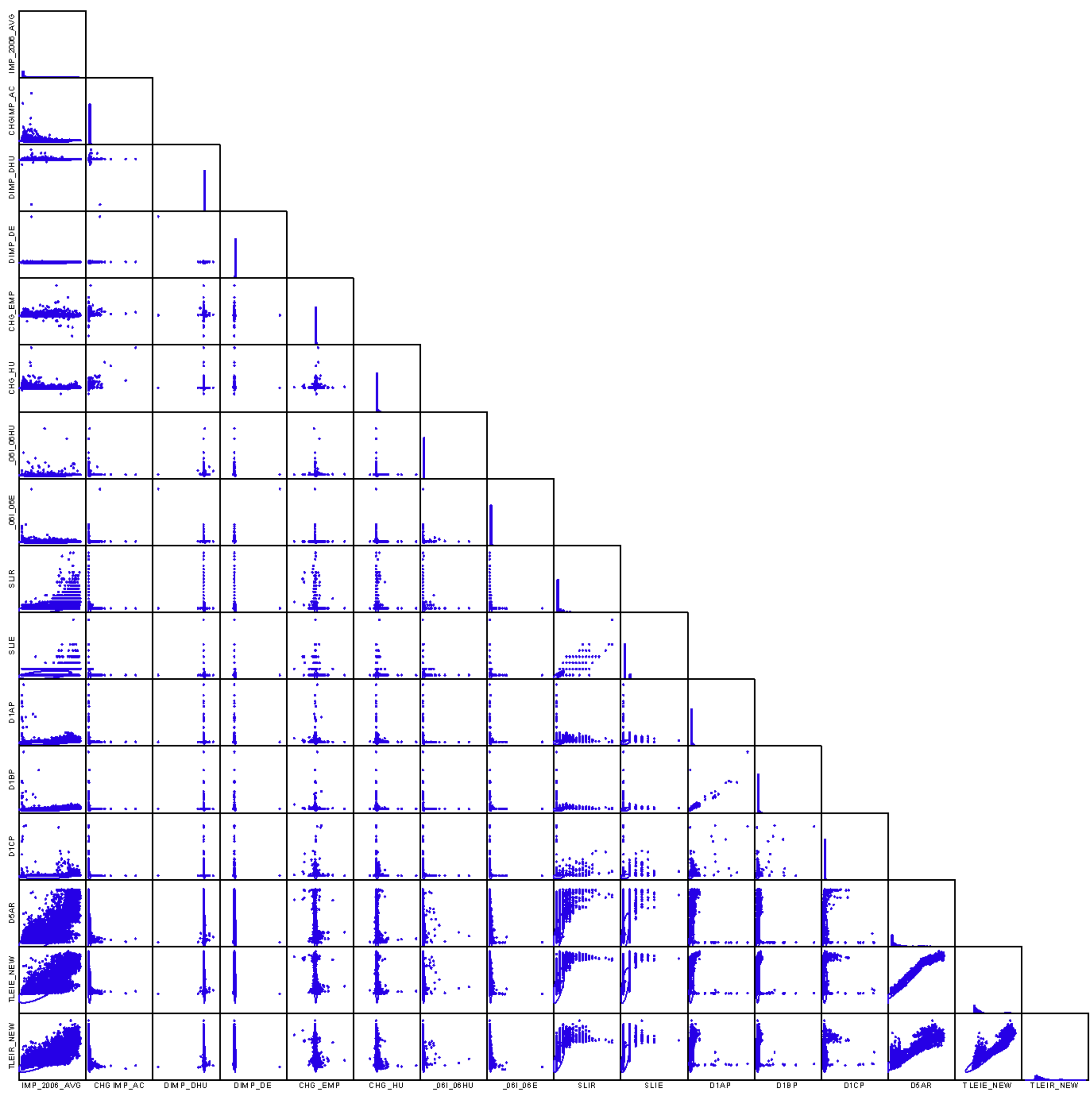
LEHD = Longitudinal Employer-Household Dynamics Dataset. Accessed online, February 2011.
NLCD = NCLD 2006 impervious cover rasters and land use change rasters for 2006 and 2001-2006 change. Accessed online, February 2011.
HUD = occupied housing units survey from US Department of Housing and Urban Development, provided by EPA.
SLI = Smart Location Index, shapefile and database, (Theobald, et al., 2011), provided by EPA.
NLCD rasters spatially processed with SLI shapefile using ESRI ArcGIS Spatial Analyst and STARSPAN algorithms
Bhatt, N., Peppard, C., and S. Potts, 2009. Getting Back on Track: Aligning State Transportation Policy with Climate Change Goals. Natural Resources Defense Council December 2010. http://www.nrdc.org/smartgrowth/files/GettingBackonTrack_report.pdf.

Exhibit B-7: Correlation Analysis and SPLOM for Filter 1

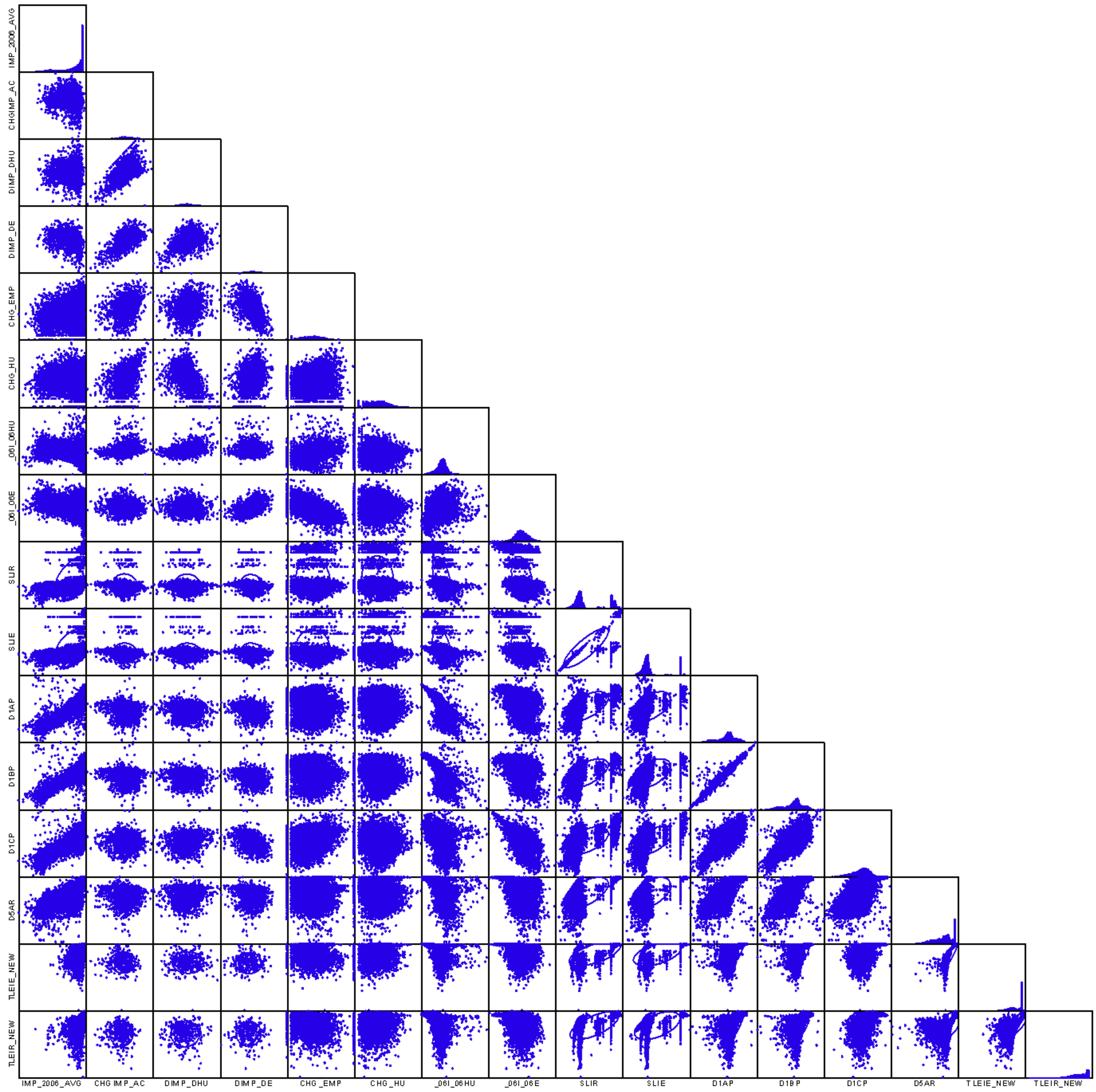
Filter 1 - Random subset of all data (1/3rd of data points)

Spearman's Rho Correlation Coefficients

	IMP_2006 _AVG	CHGIMP _AC	DIMP _DHU	DIMP _DE	CHG _EMP	CHG _HU	06I _06HU	06I _06E	SLIR	SLIE	D1AP	D1BP	D1CP	D5AR	TLEIE _NEW	TLEIR _NEW
IMP_2006_AVG	1.00	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
CHGIMP_AC	-0.29	1.00	.	.	.	.	.	.	.	.	.	.	.	.	.	.
DIMP_DHU	-0.28	0.94	1.00	.	.	.	.	.	.	.	.	.	.	.	.	.
DIMP_DE	-0.14	0.52	0.47	1.00	.	.	.	.	.	.	.	.	.	.	.	.
CHG_EMP	-0.05	0.23	0.21	0.47	1.00	.	.	.	.	.	.	.	.	.	.	.
CHG_HU	-0.19	0.28	0.29	0.17	0.08	1.00	.	.	.	.	.	.	.	.	.	.
_06I_06HU	-0.49	0.36	0.34	0.20	0.20	0.00	1.00	.	.	.	.	.	.	.	.	.
_06I_06E	-0.32	0.00	0.00	0.02	-0.16	-0.03	0.14	1.00	.	.	.	.	.	.	.	.
SLIR	0.71	-0.25	-0.24	-0.13	-0.07	-0.11	-0.49	-0.34	1.00	.	.	.	.	.	.	.
SLIE	0.68	-0.23	-0.22	-0.12	-0.05	-0.11	-0.46	-0.34	0.92	1.00	.	.	.	.	.	.
D1AP	0.88	-0.32	-0.30	-0.15	-0.09	-0.16	-0.72	-0.25	0.70	0.67	1.00	.	.	.	.	.
D1BP	0.88	-0.32	-0.30	-0.15	-0.09	-0.18	-0.70	-0.25	0.68	0.64	0.98	1.00	.	.	.	.
D1CP	0.76	-0.13	-0.13	-0.06	0.05	-0.11	-0.30	-0.63	0.65	0.63	0.68	0.67	1.00	.	.	.
D5AR	0.81	-0.24	-0.22	-0.11	-0.05	-0.17	-0.55	-0.27	0.56	0.49	0.78	0.81	0.62	1.00	.	.
TLEIE_NEW	0.87	-0.29	-0.27	-0.14	-0.07	-0.20	-0.59	-0.30	0.67	0.62	0.84	0.87	0.68	0.96	1.00	.
TLEIR_NEW	0.88	-0.35	-0.33	-0.19	-0.11	-0.19	-0.59	-0.34	0.83	0.77	0.85	0.86	0.72	0.81	0.92	1.00



Filter 1 Scatter Plot Matrix - Untransformed



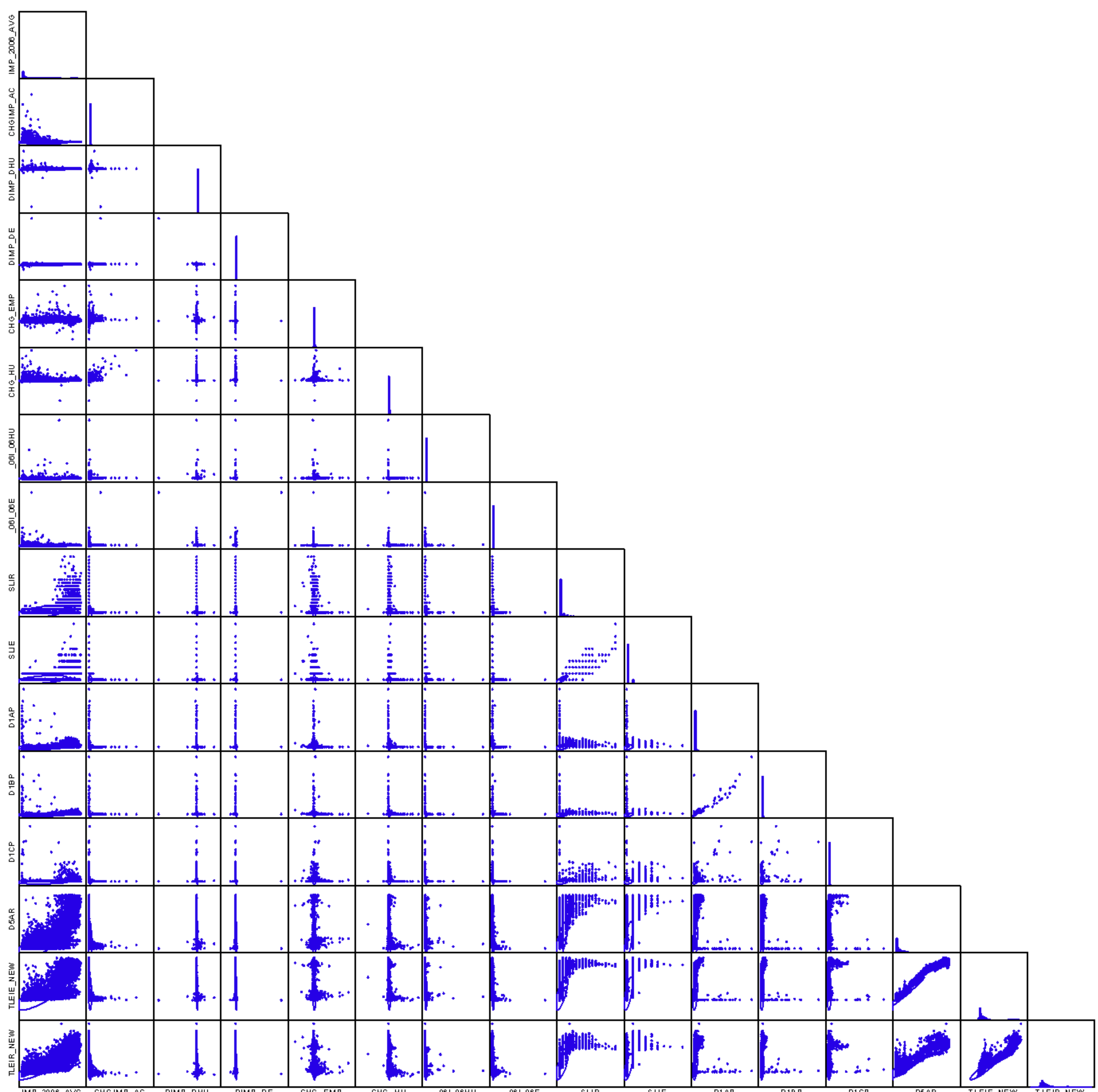
Filter 1 Scatter Plot Matrix – Log Transformed

Exhibit B-8: Correlation Analysis and SPLOM for Filter 2

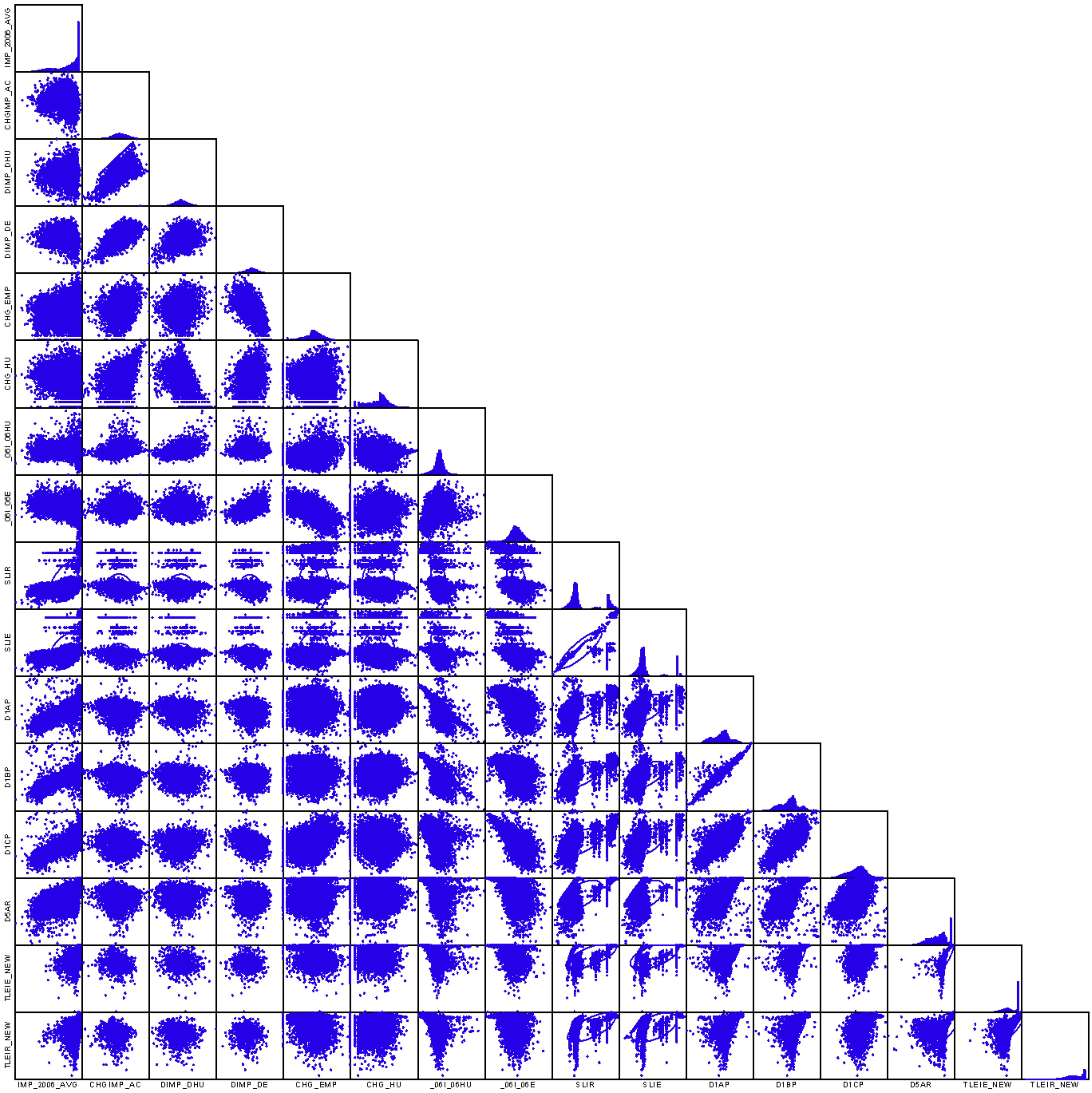
Filter 2 - Significant development/redevelopment

Spearman's Rho Correlation Coefficients

	IMP_2006 _AVG	CHGIMP _AC	DIMP _DHU	DIMP _DE	CHG _EMP	CHG _HU	06I _06HU	06I _06E	SLIR	SLIE	D1AP	D1BP	D1CP	D5AR	TLEIE _NEW	TLEIR _NEW
IMP_2006_AVG	1.00	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
CHGIMP_AC	-0.31	1.00	.	.	.	.	.	.	.	.	.	.	.	.	.	.
DIMP_DHU	-0.27	0.90	1.00	.	.	.	.	.	.	.	.	.	.	.	.	.
DIMP_DE	-0.13	0.51	0.44	1.00	.	.	.	.	.	.	.	.	.	.	.	.
CHG_EMP	0.16	0.02	-0.02	0.37	1.00	.	.	.	.	.	.	.	.	.	.	.
CHG_HU	-0.17	0.13	0.03	0.11	-0.23	1.00	.	.	.	.	.	.	.	.	.	.
_06I_06HU	-0.36	0.39	0.36	0.20	0.22	-0.17	1.00	.	.	.	.	.	.	.	.	.
_06I_06E	-0.46	0.19	0.16	0.13	-0.36	0.20	0.18	1.00	.	.	.	.	.	.	.	.
SLIR	0.75	-0.30	-0.26	-0.16	0.08	-0.13	-0.37	-0.41	1.00	.	.	.	.	.	.	.
SLIE	0.73	-0.29	-0.25	-0.15	0.10	-0.13	-0.35	-0.41	0.94	1.00	.	.	.	.	.	.
D1AP	0.88	-0.30	-0.28	-0.12	0.08	-0.08	-0.60	-0.37	0.70	0.68	1.00	.	.	.	.	.
D1BP	0.88	-0.29	-0.27	-0.11	0.08	-0.10	-0.58	-0.37	0.69	0.67	0.98	1.00	.	.	.	.
D1CP	0.84	-0.22	-0.20	-0.12	0.26	-0.21	-0.24	-0.70	0.68	0.67	0.75	0.74	1.00	.	.	.
D5AR	0.78	-0.24	-0.20	-0.10	0.08	-0.12	-0.44	-0.38	0.54	0.49	0.74	0.77	0.66	1.00	.	.
TLEIE_NEW	0.86	-0.29	-0.25	-0.14	0.09	-0.15	-0.48	-0.44	0.70	0.66	0.83	0.85	0.74	0.94	1.00	.
TLEIR_NEW	0.87	-0.38	-0.33	-0.20	0.06	-0.17	-0.49	-0.47	0.85	0.81	0.84	0.84	0.77	0.74	0.90	1.00



Filter 2 Scatter Plot Matrix - Untransformed



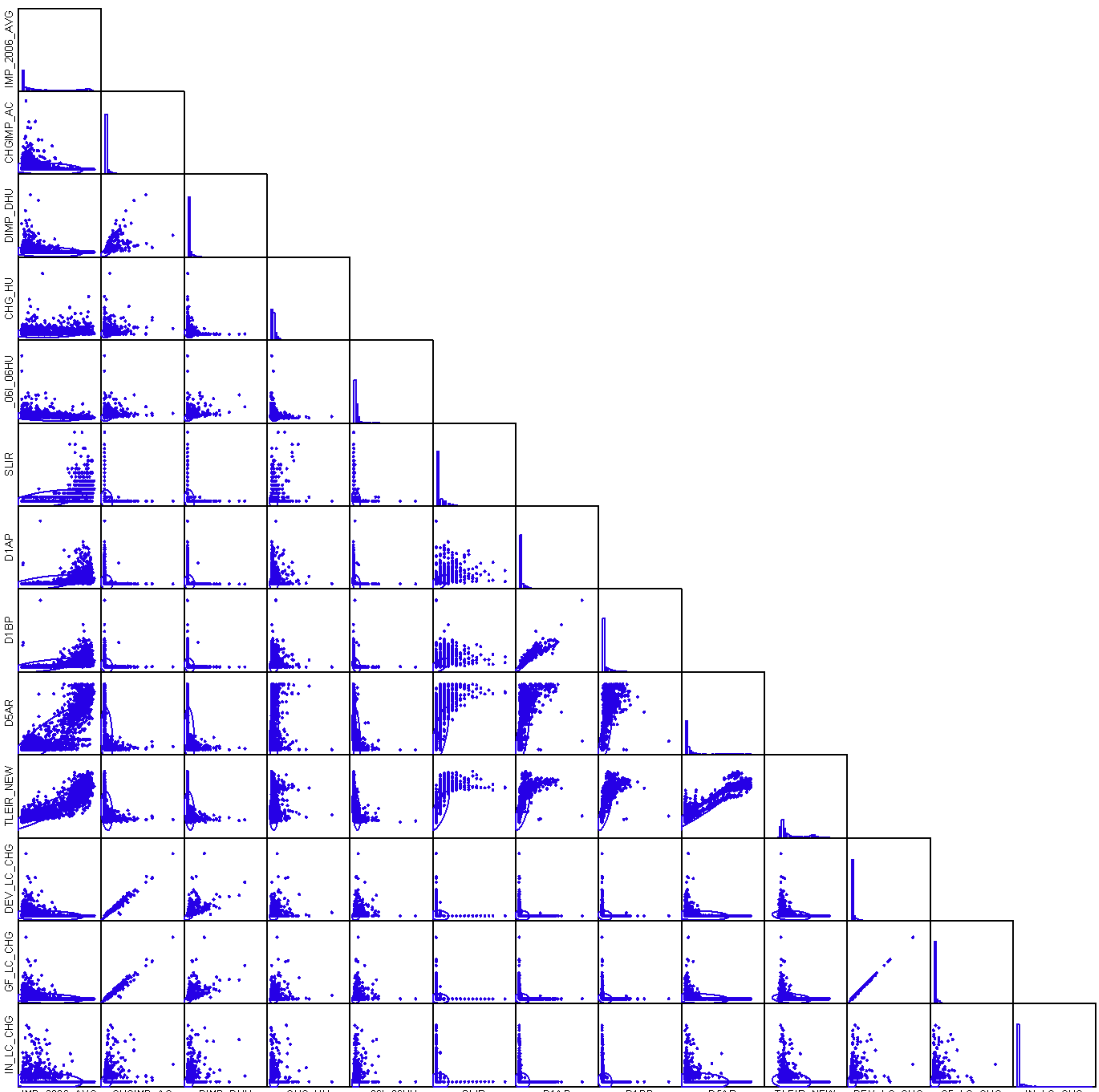
Filter 2 Scatter Plot Matrix – Log Transformed (zeros not shown)

Exhibit B-9: Correlation Analysis and SPLOM for Filter 3

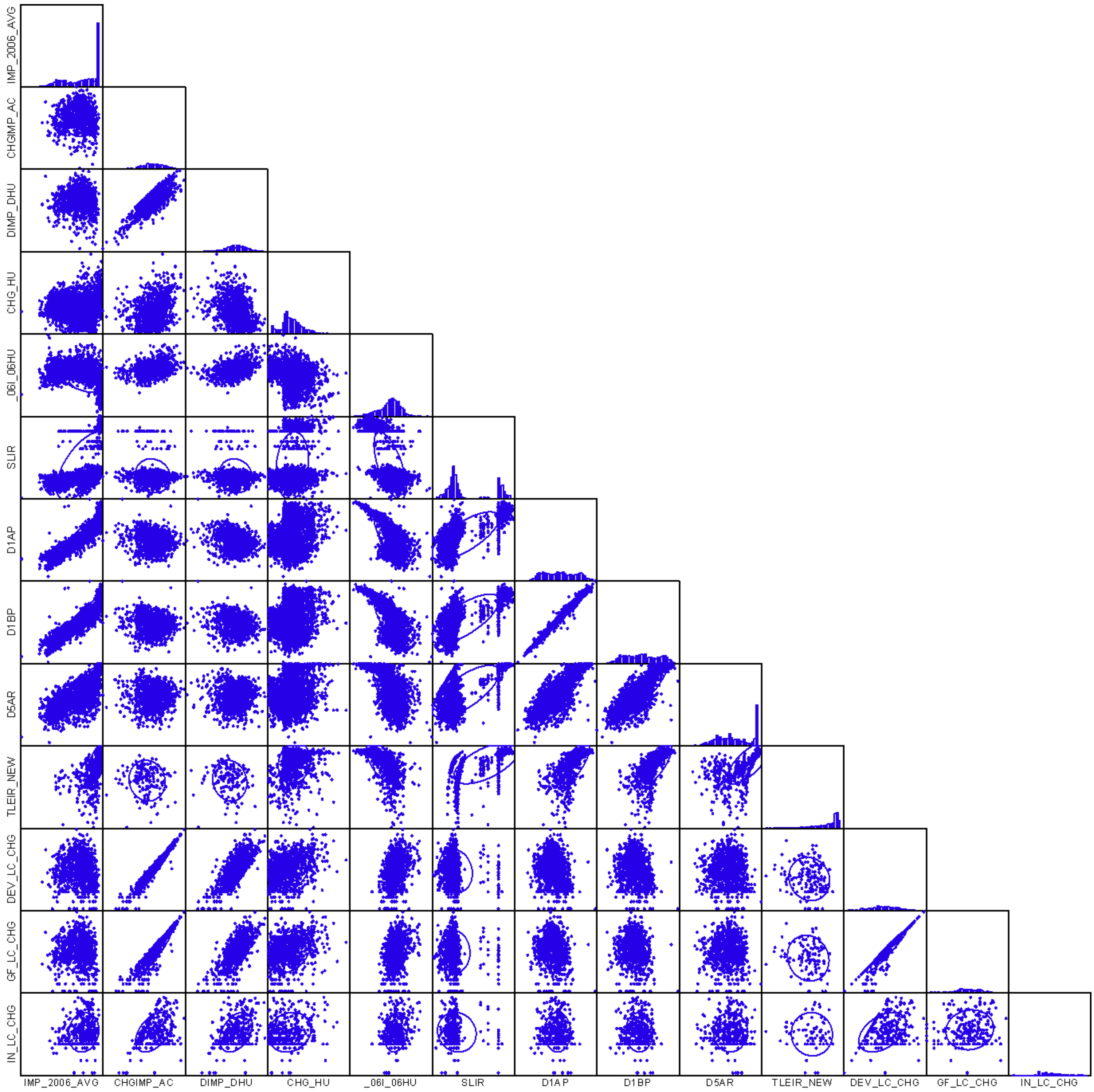
Filter 3 - Dominant Residential Change

Spearman's Rho Correlation Coefficients

	IMP_2006 _AVG	CHGIMP _AC	DIMP_DH U	CHG_HU	_06I_06HU	SLIR	D1AP	D1BP	D5AR	TLEIR _NEW	DEV_LC _CHG	GF_LC _CHG	IN_LC _CHG
IMP_2006_AVG	1.00	.	.	.	.	.	.	.	.	.	.	.	.
CHGIMP_AC	-0.21	1.00	.	.	.	.	.	.	.	.	.	.	.
DIMP_DHU	-0.21	0.99	1.00	.	.	.	.	.	.	.	.	.	.
CHG_HU	0.10	-0.17	-0.28	1.00	.	.	.	.	.	.	.	.	.
_06I_06HU	-0.53	0.49	0.50	-0.19	1.00	.	.	.	.	.	.	.	.
SLIR	0.78	-0.24	-0.24	0.09	-0.52	1.00	.	.	.	.	.	.	.
D1AP	0.95	-0.24	-0.24	0.13	-0.69	0.77	1.00	.	.	.	.	.	.
D1BP	0.95	-0.24	-0.24	0.12	-0.68	0.75	0.99	1.00	.	.	.	.	.
D5AR	0.84	-0.22	-0.22	0.12	-0.62	0.63	0.85	0.86	1.00	.	.	.	.
TLEIR_NEW	0.90	-0.29	-0.29	0.08	-0.62	0.85	0.91	0.90	0.79	1.00	.	.	.
DEV_LC_CHG	-0.21	0.99	0.98	-0.18	0.48	-0.24	-0.24	-0.23	-0.21	-0.29	1.00	.	.
GF_LC_CHG	-0.21	0.93	0.91	-0.13	0.47	-0.23	-0.24	-0.24	-0.21	-0.29	0.94	1.00	.
IN_LC_CHG	-0.03	0.50	0.50	-0.12	0.23	-0.09	-0.05	-0.05	-0.06	-0.07	0.49	0.29	1.00



Filter 3 Scatter Plot Matrix - Untransformed



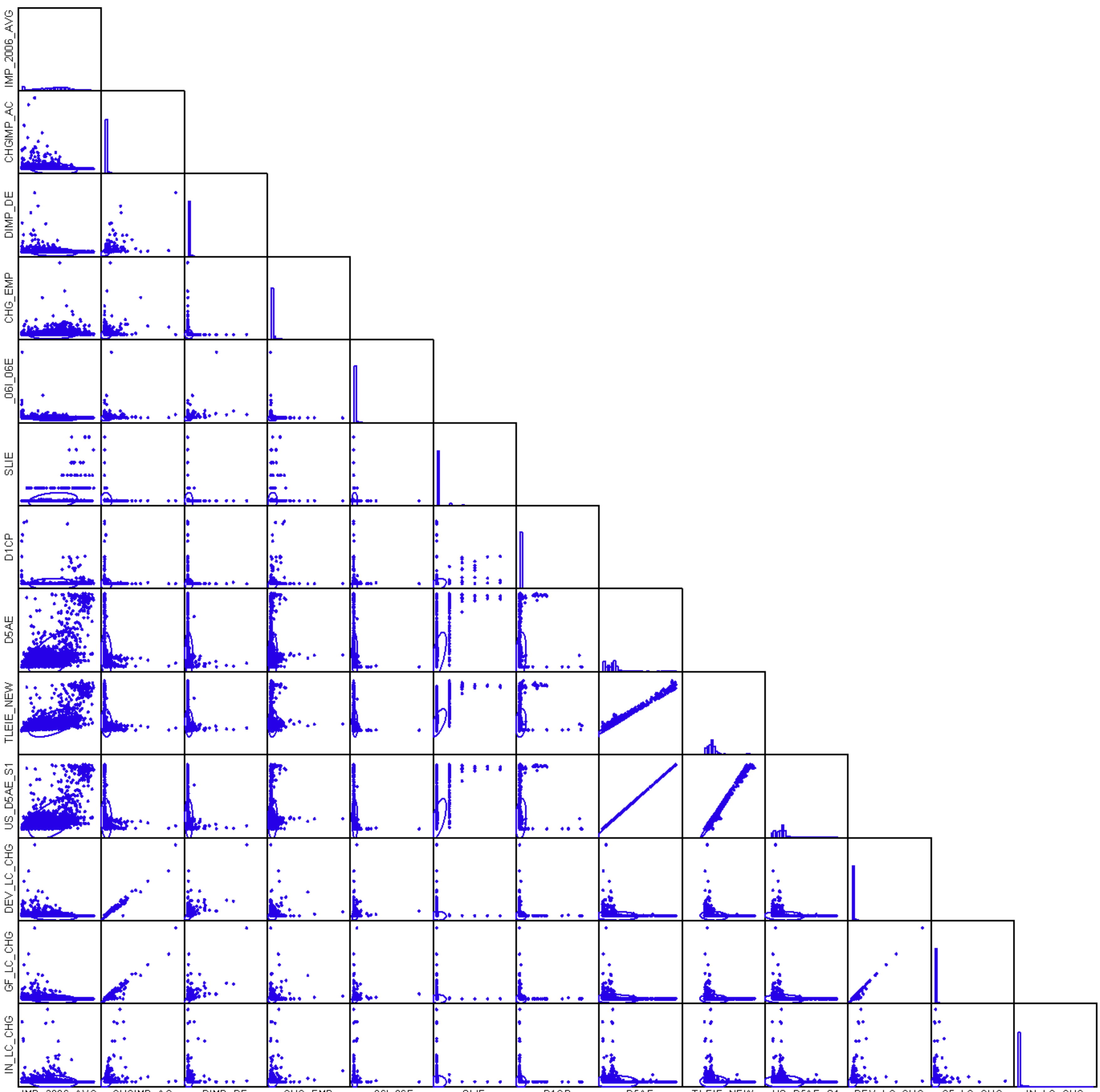
Filter 3 Scatter Plot Matrix – Log Transformed (zeros not shown)

Exhibit B-10: Correlation Analysis and SPLOM for Filter 4

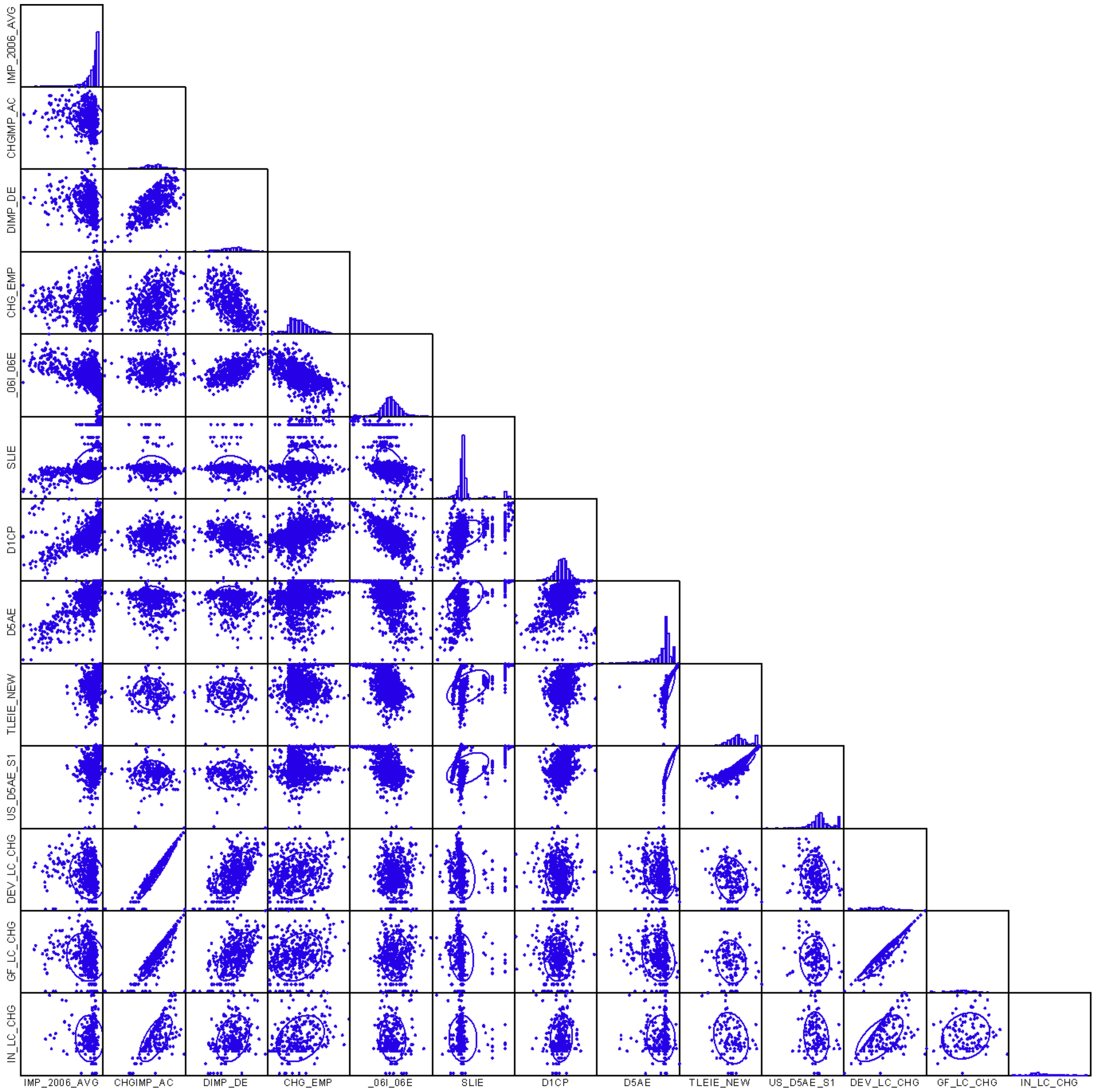
Filter 4 - Dominant Employment Change

Spearman's Rho Correlation Coefficients

	IMP_200 6 _AVG	CHGIMP _AC	DIMP _DE	CHG _EMP	_06I _06E	SLIE	D1CP	D5AE	TLEIE _NEW	US_D5AE _S1	DEV_LC _CHG	GF_LC _CHG	IN_LC _CHG
IMP_2006_AV G	1.00	.	.	.	.	.	.	.	.	.	.	.	.
CHGIMP_AC	-0.40	1.00	.	.	.	.	.	.	.	.	.	.	.
DIMP_DE	-0.41	0.98	1.00	.	.	.	.	.	.	.	.	.	.
CHG_EMP	0.24	-0.10	-0.20	1.00	.	.	.	.	.	.	.	.	.
_06I_06E	-0.32	0.25	0.30	-0.55	1.00	.	.	.	.	.	.	.	.
SLIE	0.50	-0.30	-0.29	0.11	-0.28	1.00	.	.	.	.	.	.	.
D1CP	0.52	-0.21	-0.25	0.45	-0.65	0.39	1.00	.	.	.	.	.	.
D5AE	0.56	-0.32	-0.32	0.10	-0.30	0.25	0.32	1.00	.	.	.	.	.
TLEIE_NEW	0.62	-0.37	-0.37	0.10	-0.32	0.40	0.36	0.97	1.00	.	.	.	.
US_D5AE_S1	0.56	-0.32	-0.32	0.10	-0.30	0.25	0.32	1.00	0.97	1.00	.	.	.
DEV_LC_CHG	-0.38	0.97	0.95	-0.11	0.26	-0.30	-0.20	-0.30	-0.35	-0.30	1.00	.	.
GF_LC_CHG	-0.37	0.85	0.83	-0.10	0.26	-0.30	-0.22	-0.30	-0.35	-0.30	0.88	1.00	.
IN_LC_CHG	-0.19	0.62	0.59	-0.01	0.07	-0.15	-0.03	-0.12	-0.15	-0.12	0.62	0.31	1.00



Filter 4 Scatter Plot Matrix - Untransformed



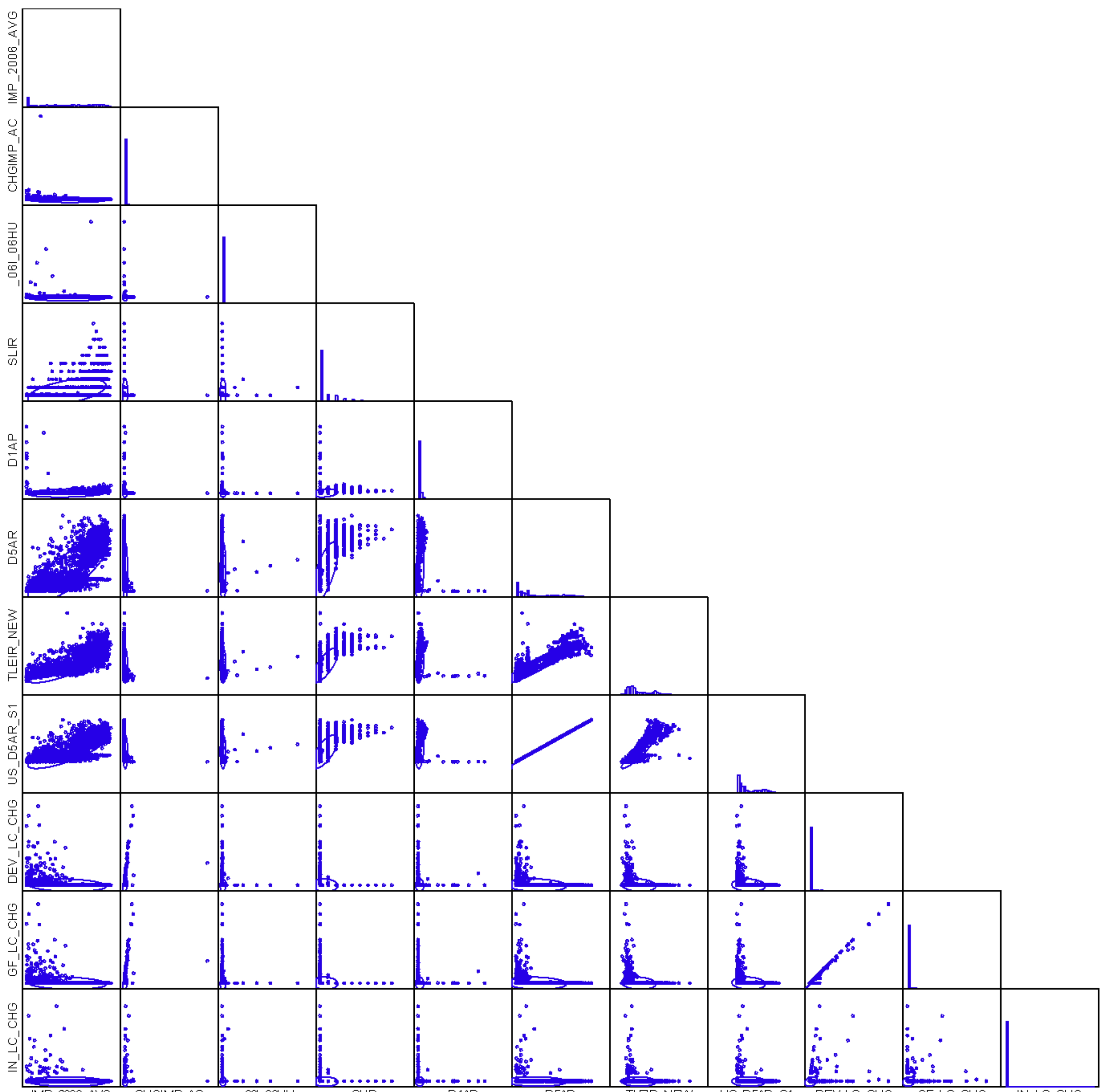
Filter 4 Scatter Plot Matrix – Log Transformed (zeros not shown)

Exhibit B-11: Correlation Analysis and SPLOM for Filter 5

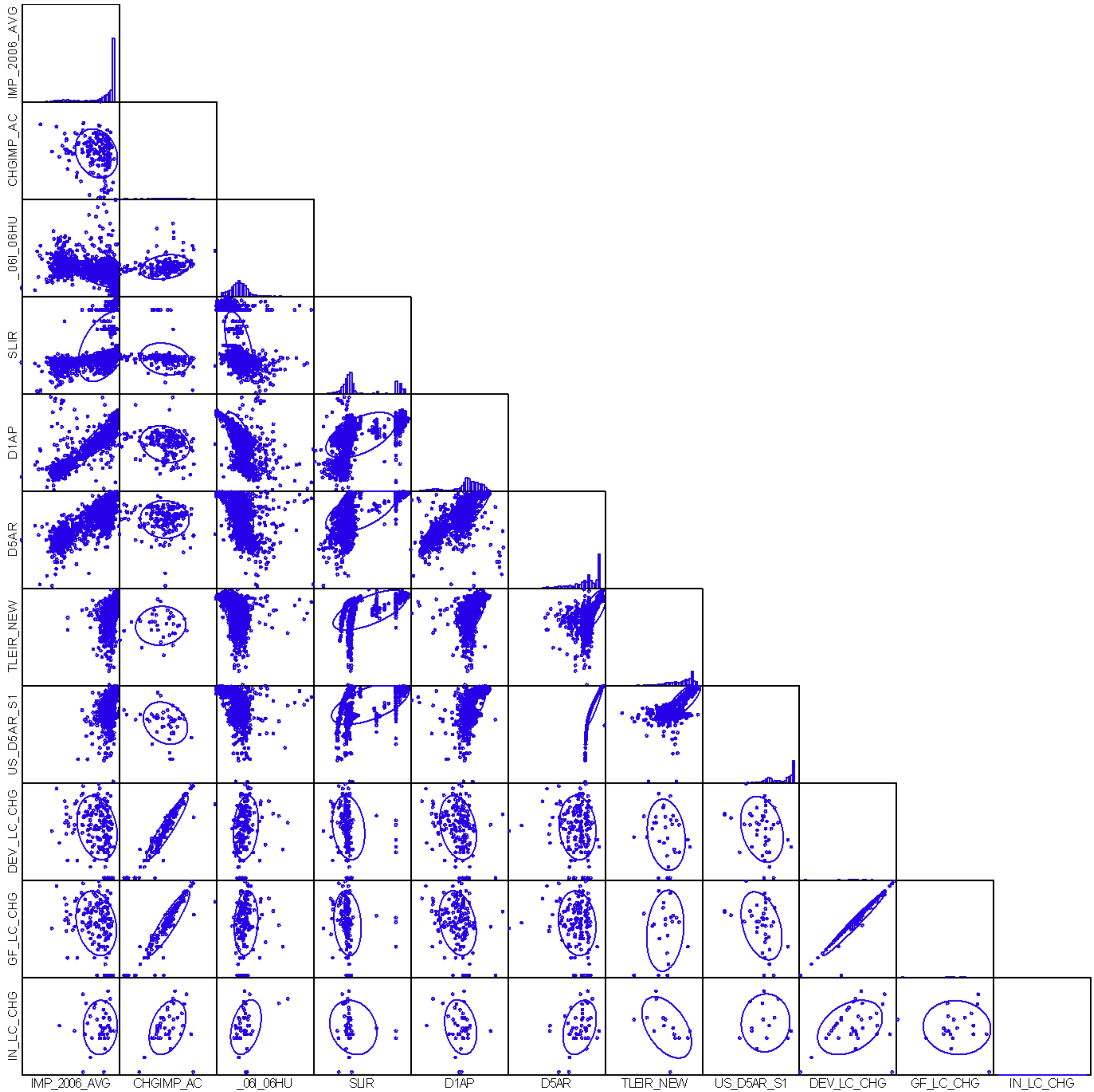
Filter 5 - Residential Dominated CBG in 2006

Spearman's Rho Correlation Coefficients

	IMP_2006_AVG	CHGIMP_AC	_06I_06HU	SLIR	D1AP	D5AR	TLEIR_NEW	US_D5AR_S1	DEV_LC_CHG	GF_LC_CHG	IN_LC_CHG
IMP_2006_AVG	1.00	.	.	.	.	.	.	.	.	.	.
CHGIMP_AC	-0.24	1.00	.	.	.	.	.	.	.	.	.
_06I_06HU	-0.61	0.23	1.00	.	.	.	.	.	.	.	.
SLIR	0.64	-0.15	-0.63	1.00	.	.	.	.	.	.	.
D1AP	0.86	-0.23	-0.78	0.68	1.00	.	.	.	.	.	.
D5AR	0.86	-0.21	-0.65	0.60	0.80	1.00	.	.	.	.	.
TLEIR_NEW	0.88	-0.25	-0.68	0.78	0.84	0.90	1.00	.	.	.	.
US_D5AR_S1	0.86	-0.21	-0.65	0.60	0.80	1.00	0.90	1.00	.	.	.
DEV_LC_CHG	-0.22	0.95	0.21	-0.15	-0.21	-0.19	-0.24	-0.19	1.00	.	.
GF_LC_CHG	-0.22	0.89	0.21	-0.15	-0.20	-0.18	-0.23	-0.18	0.93	1.00	.
IN_LC_CHG	-0.10	0.47	0.10	-0.03	-0.10	-0.08	-0.08	-0.08	0.49	0.25	1.00



Filter 5 Scatter Plot Matrix - Untransformed



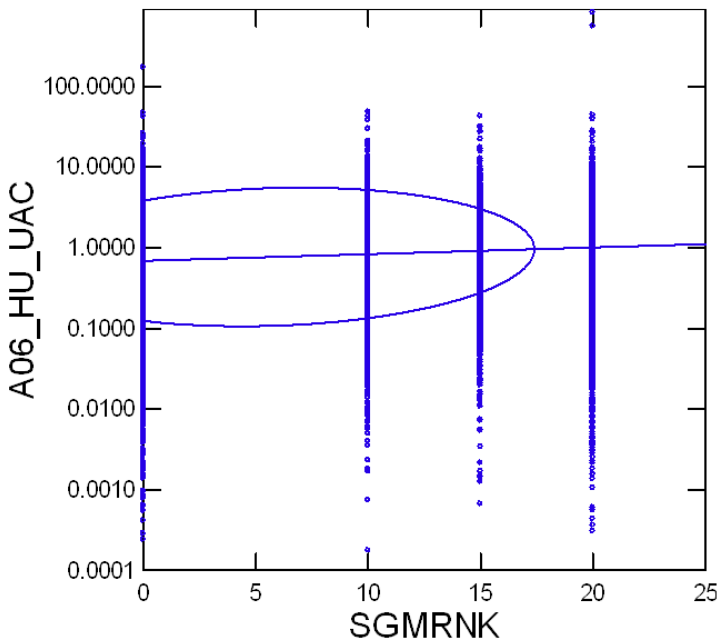
Filter 5 Scatter Plot Matrix – Log Transformed (zeros not show)

Exhibit B-12: Evaluation of Growth Management Policy (SGMRNK) as Possible Predictive or Stratification Variable

To evaluate what level of influence that strength of state growth management policy may have on model predictions, the final regression dataset was filtered for the CBGs within the jurisdiction of metropolitan planning organizations (MPOs) and where there the NCLD 2001-2006 land cover change dataset detected land cover change from open space to urban development. As can be seen from the correlation plot, a slight positive relationship was detected between strength of urban growth management rank (SGMRNK) and housing units per acre in 2006 (A06_HU_UAC). Housing density is used as an indicator of overall development density. *Note: the final regression dataset variable names used in this exhibit are somewhat different than the variables names used in the preliminary analysis dataset described in previous exhibits.*

This analysis suggests that recent development that caused land cover change has been somewhat higher density on average in states with stronger growth management policies. However, the range of predictions is still very large compared to the preliminary trend. Also, it is not possible to determine from this correlation whether a stronger growth management boundary resulted in higher density development at the urban fringe in these states versus a greater portion of development occurring in more centrally located areas where higher density development would be expected.

```
SELECT (MPO_NAME$ <> '') AND (A01_06_CHDEV123AC > 0)
```



Dependent Variable	A06_HU_UAC
N	32,677
Multiple R	0.054
Squared Multiple R	0.003
Adjusted Squared Multiple R	0.003
Standard Error of Estimate	5.830

Regression Coefficients $B = (X'X)^{-1}X'Y$

Effect	Coefficient	Standard Error	Std. Coefficient	Tolerance	t	p-value
CONSTANT	1.265	0.040	0.000	.	31.541	0.000
SGMRNK	0.041	0.004	0.054	1.000	9.799	0.000

Analysis of Variance

Source	SS	df	Mean Squares	F-ratio	p-value
Regression	3,263.630	1	3,263.630	96.019	0.000
Residual	1,110,606.105	32,675	33.989		

Number of Observations: 32,677

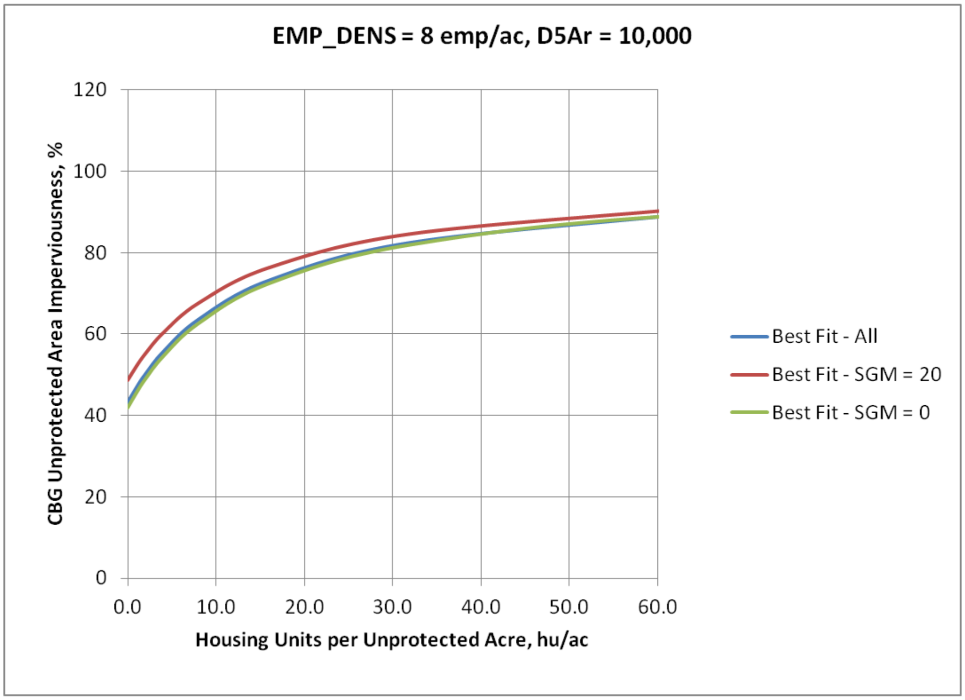
Spearman Correlation Matrix

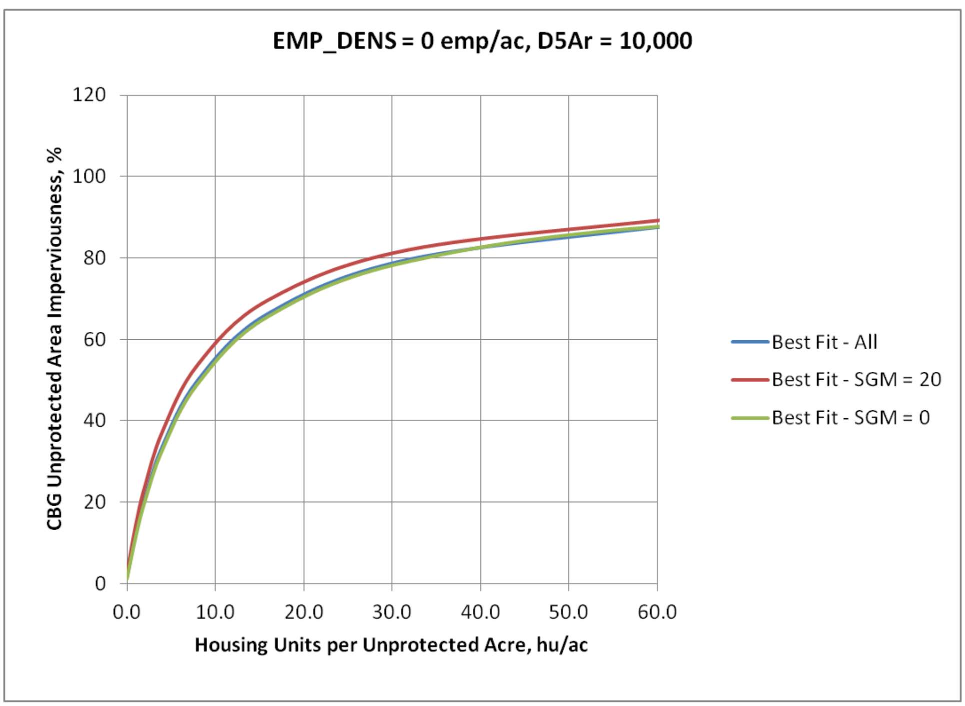
	A06_HU_UAC	SGMRNK
A06_HU_UAC	1.000	
SGMRNK	0.141	1.000

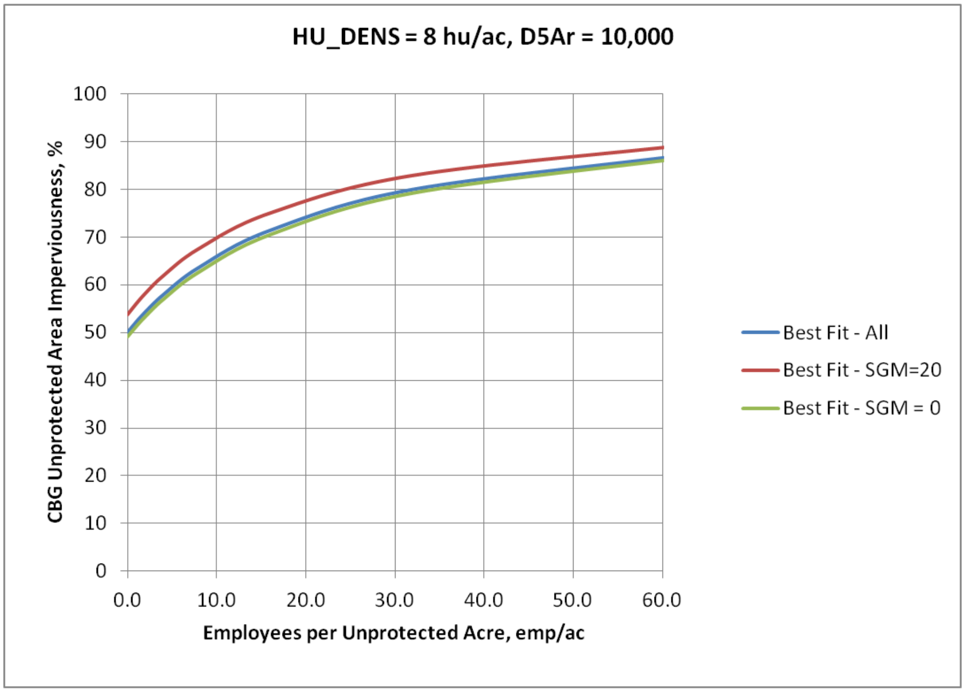
Because SGMRNK is based on arbitrary numeric values assigned to qualitative ranking, it is not an appropriate model variable. However, it may be used as a stratification variable. To evaluate the possible benefit of including SGMRNK as a stratification variable, the form of the best fit regression model obtained for the entire dataset (See Report Section 3.3) was applied to subsets of the dataset filtered for SGMRNK=20 and SGMRNK=0. New model coefficients were estimated for each of these subsets. Example plots from the resulting best fit models are shown on the following pages.

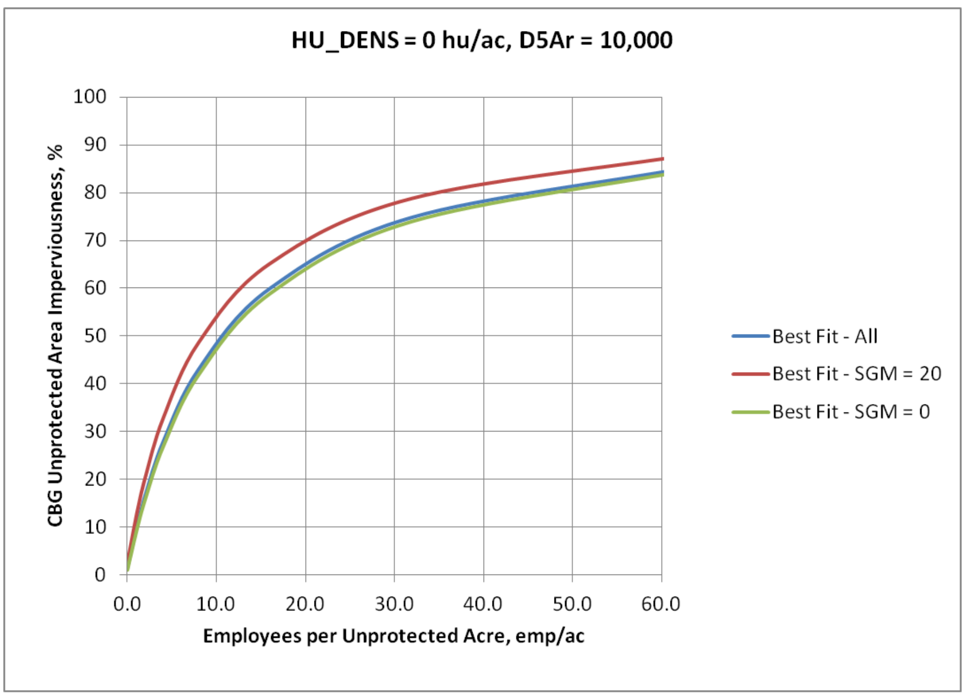
In general, the resulting models followed a very similar shape and had similar regression statistics. The shape of the curve (i.e., slope at a given point) is the most important indicator of the ISG that will be predicted. The similarity of shapes between models developed for different subsets indicates that each subset model would be expected to return similar estimates; therefore significant benefit would not be gained through stratification on SMGRNK.

The subset with SGMRNK=20 had somewhat higher estimates of imperviousness of for a given density of development than the subset with SGMRNK=0 and the entire dataset. This is somewhat unexpected and is not likely a reliable trend upon which to stratify estimates of future development. The SGMRNK is a qualitative and somewhat subjective measure of growth management policies at the state level in 2009. However, these rankings in 2009 may not be indicative the growth policies and economic/geographic forces that affected the patterns of the majority of historic development activity up to the present. Refinement of SMGRNK and further evaluation of its possible application in the ISGM is recommended for further efforts.






HU_DENS = 8 hu/ac, D5Ar = 10,000
CBG Unprotected Area Imperviousness, %
Employees per Unprotected Acre, emp/ac
0
10
20
30
40
50
60
70
80
90
100
0.0
10.0
20.0
30.0
40.0
50.0
60.0
Best Fit - All
Best Fit - SGM=20
Best Fit - SGM = 0


HU_DENS = 0 hu/ac, D5Ar = 10,000
CBG Unprotected Area Imperviousness, %
Employees per Unprotected Acre, emp/ac
0
10
20
30
40
50
60
70
80
90
100
0.0
10.0
20.0
30.0
40.0
50.0
60.0
Best Fit - All
Best Fit - SGM = 20
Best Fit - SGM = 0

Appendix C

Plots of Hypothetical Model Application to Selected CBGs for Model Validation

Model Application

The ISGM was applied two times to a selection of CBGs assuming hypothetical increases of 100 housing units and 100 employees, separately. The predicted increases in impervious surface associated with these increases were normalized by the 100 units to yield a hypothetical increase in impervious surface per unit. The exhibits allow a visual inspection of the reasonableness of these estimates relative to the conditions of the CBG and the context of the CBG within the urban area. Note that photography is generally from 2010 or 2011 and baseline conditions are based on circa 2006, therefore baseline conditions may not precisely match photography.

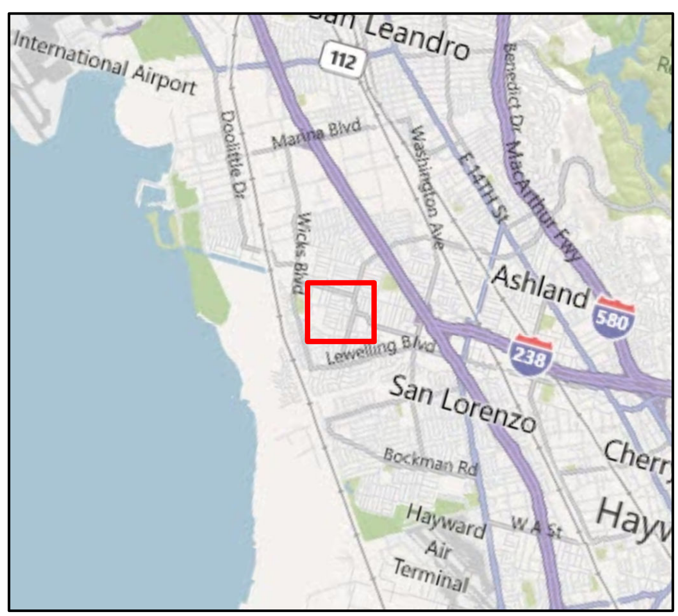
Key to Exhibits

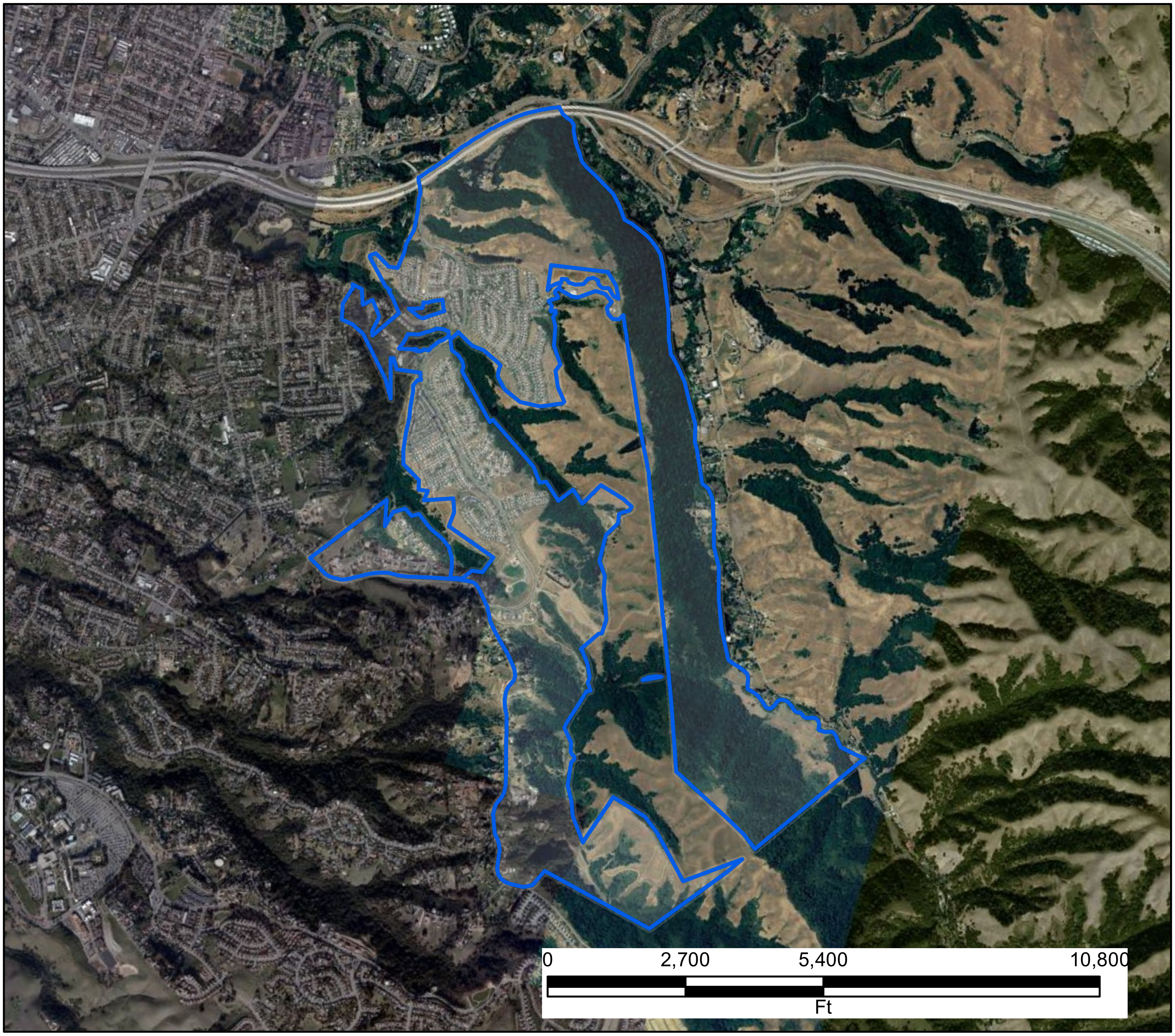
Example Legend Entry	Key
CBG: 060014335002	CBG ID
San Francisco-Oakland-Fremont, CA	MSA that CBG is located within
Baseline hu/ac: 5.38	Housing unit density, unprotected area, looked up from database (2006)[1]
Baseline emp/ac: 6.13	Employment density, unprotected area, looked up from database (2009)
D5Ar: 407831	Destination accessibility, looked up from database (2009)
Net ISGr = 0.017 IAC/hu (756 ISF/hu)	Net impervious surface growth predicted by the ISGM for a hypothetical addition of 100 housing units to the CBG IAC/hu = impervious acres per housing unit (ISF/hu = impervious sq-ft per housing unit)
Net ISGe = 0.013 IAC/emp (585 ISF/emp)	Net impervious surface growth predicted by the ISGM for a hypothetical addition of 100 jobs to the CBG. IAC/emp = impervious acre per added job (ISF/emp = impervious sq-ft per added job)

[1]Note, for the final tool release housing unit counts have been updated to 2010 housing units.

CBG ID: 060014335002

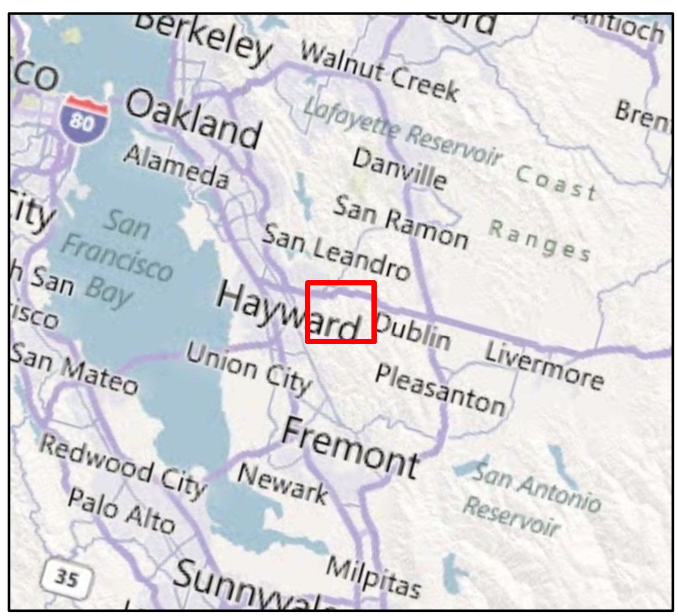
CBG: 060014335002
San Francisco-Oakland-Fremont, CA
Baseline hu/ac: 5.38
Baseline emp/ac: 6.13
D5Ar: 407831
Net ISGr = 0.017 IAC/hu
(756 ISF/hu)
Net ISGe = 0.013 IAC/emp
(585 ISF/emp





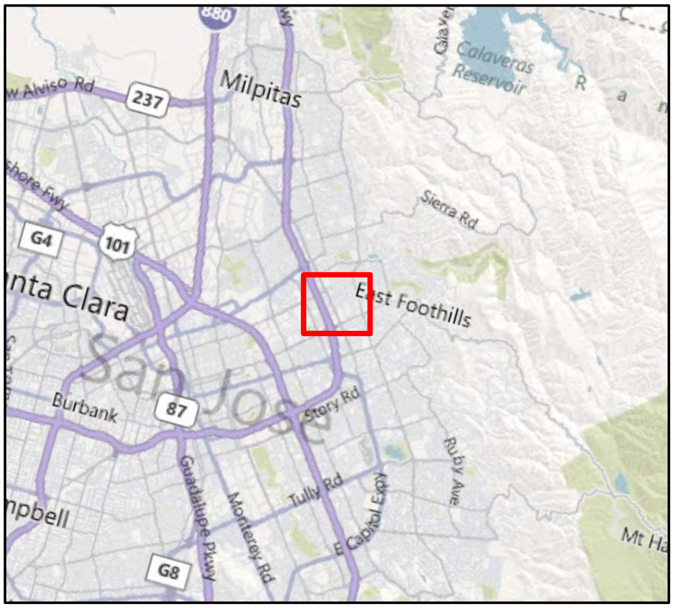
CBG ID: 060014351011

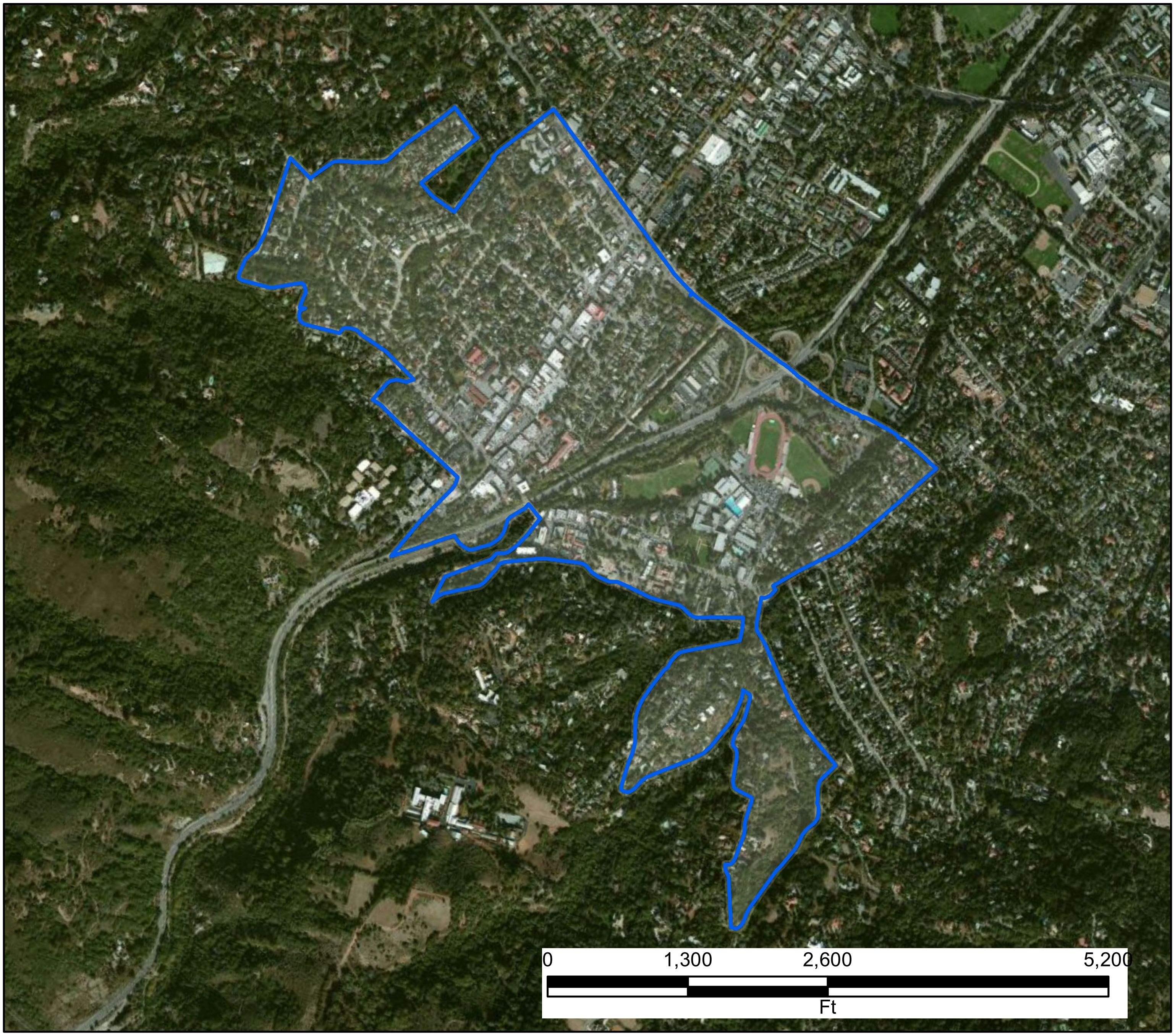
CBG: 060014351011
San Francisco-Oakland-Fremont, CA
Baseline hu/ac: 0.81
Baseline emp/ac: 0.13
D5Ar: 362346
Net ISGr = 0.063 IAC/hu
(2757 ISF/hu)
Net ISGe = 0.048 IAC/emp
(2093 ISF/emp



CBG ID: 060855038041

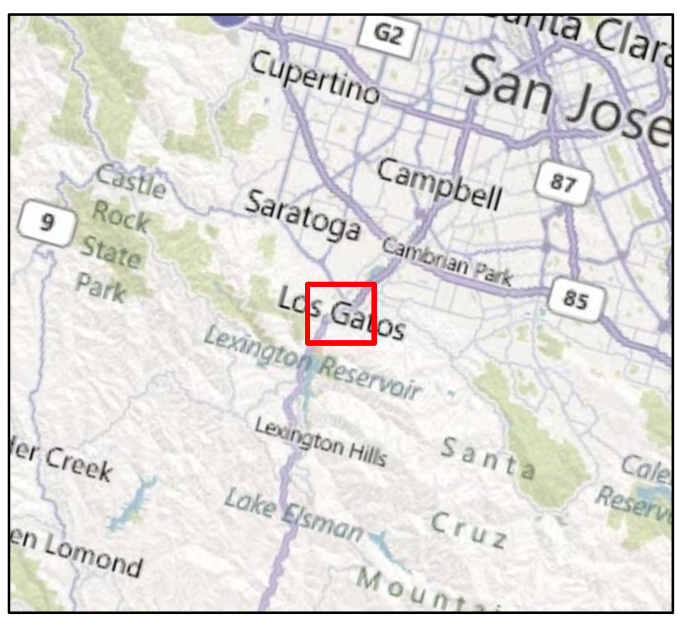
CBG: 060855038041
San Jose-Sunnyvale-Santa Clara, CA
Baseline hu/ac: 4.18
Baseline emp/ac: 4.18
D5Ar: 364511
Net ISGr = 0.025 IAC/hu
(1105 ISF/hu)
Net ISGe = 0.019 IAC/emp
(841 ISF/emp



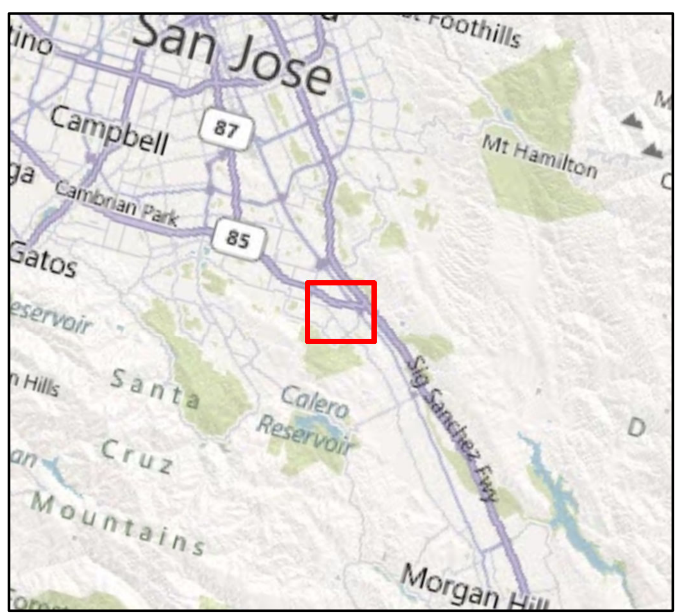


CBG ID: 060855070011

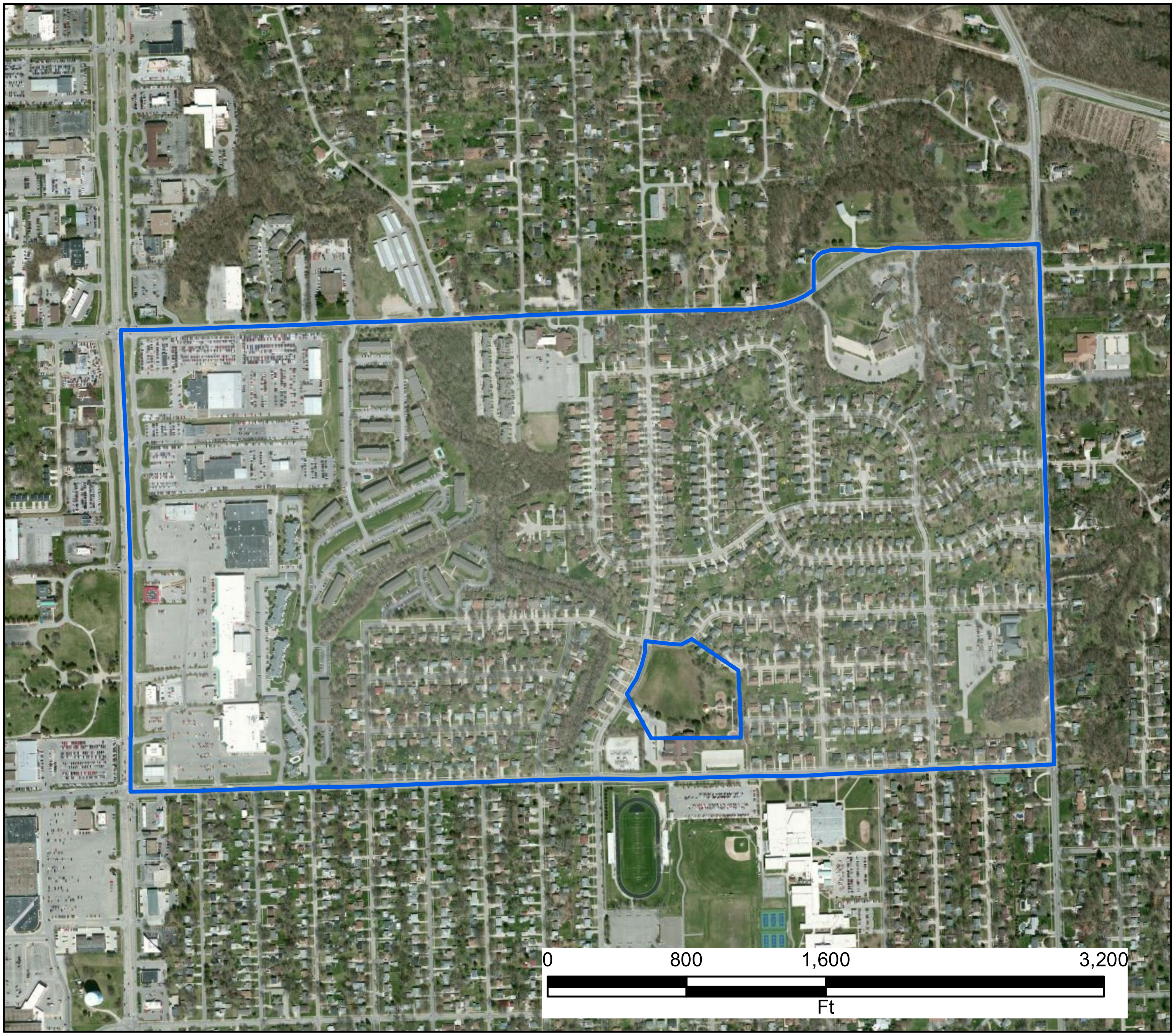
CBG: 060855070011
San Jose-Sunnyvale-Santa Clara, CA
Baseline hu/ac: 3.3
Baseline emp/ac: 7.81
D5Ar: 247434
Net ISGr = 0.022 IAC/hu
(979 ISF/hu)
Net ISGe = 0.017 IAC/emp
(744 ISF/emp



CBG ID: 060855120321

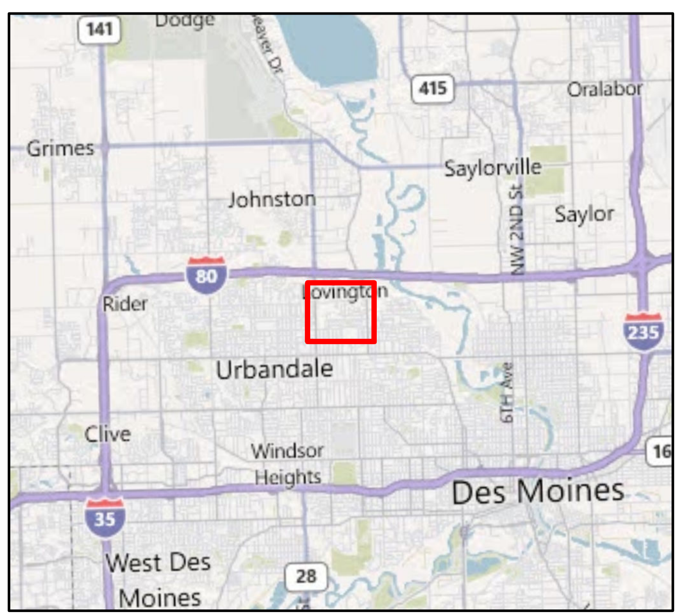


CBG: 060855120321
San Jose-Sunnyvale-Santa Clara, CA
Baseline hu/ac: 0.58
Baseline emp/ac: 7.99
D5Ar: 184593
Net ISGr = 0.032 IAC/hu
(1378 ISF/hu)
Net ISGe = 0.024 IAC/emp
(1047 ISF/emp



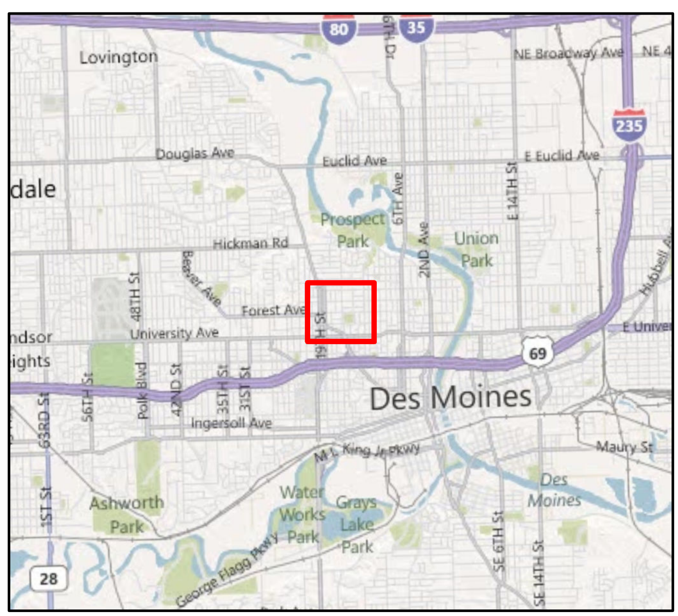
CBG ID: 191530008012

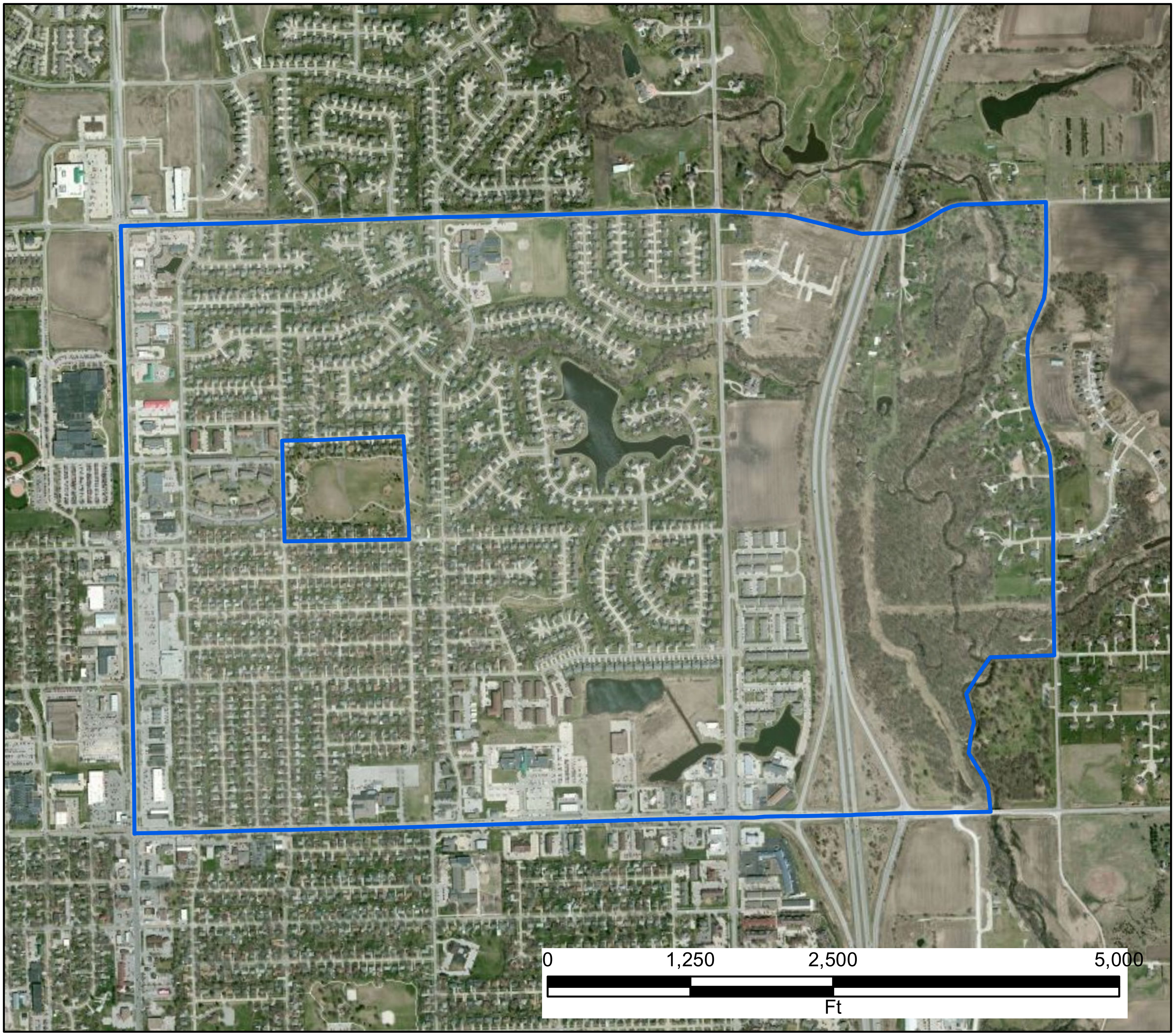
CBG: 191530008012
Des Moines-West Des Moines, IA
Baseline hu/ac: 4.21
Baseline emp/ac: 2.83
D5Ar: 164677
Net ISGr = 0.033 IAC/hu
(1439 ISF/hu)
Net ISGe = 0.025 IAC/emp
(1096 ISF/emp



CBG ID: 191530012003

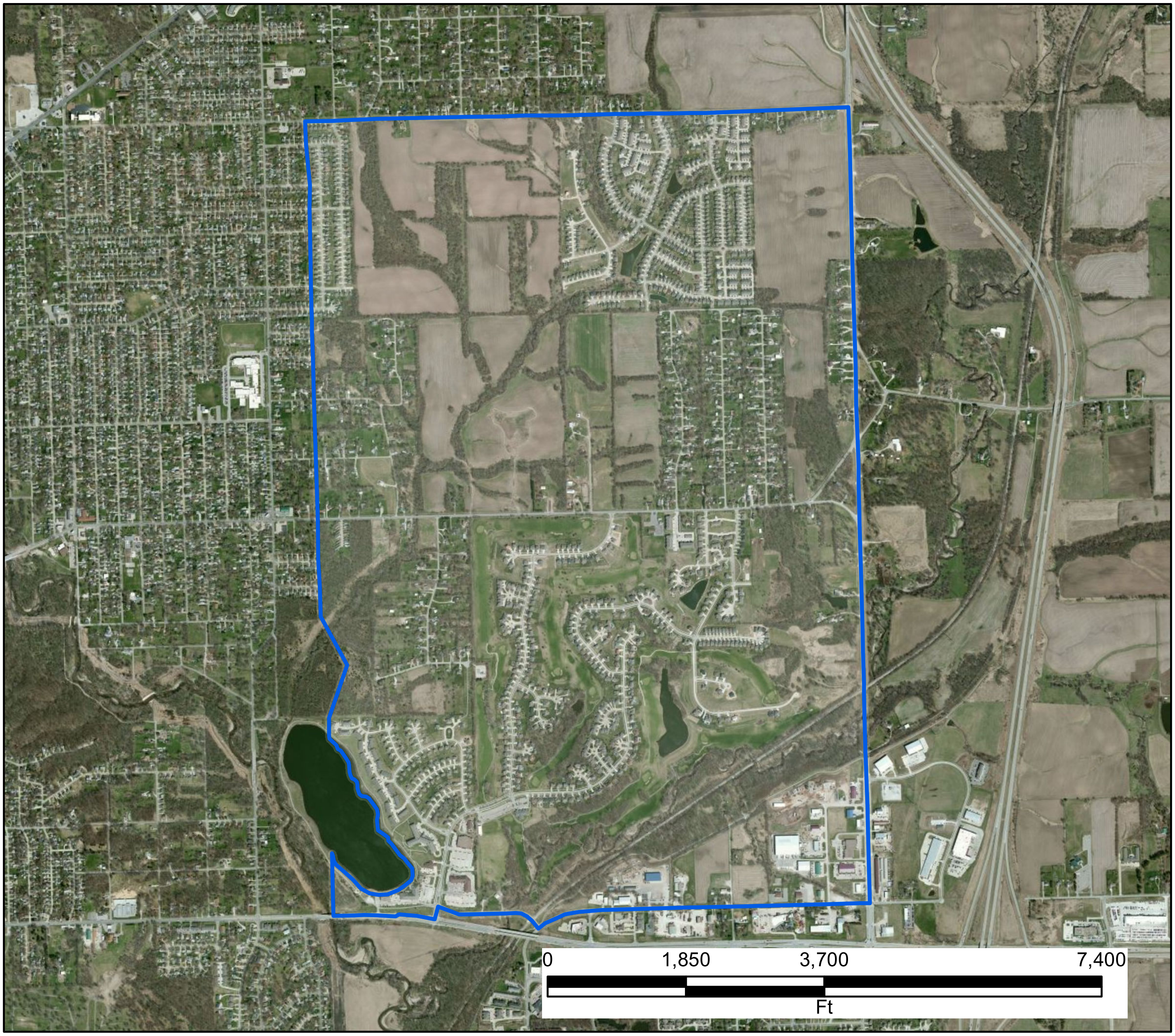
CBG: 191530012003
Des Moines-West Des Moines, IA
Baseline hu/ac: 3.9
Baseline emp/ac: 1.81
D5Ar: 189425
Net ISGr = 0.036 IAC/hu
(1587 ISF/hu)
Net ISGe = 0.028 IAC/emp
(1216 ISF/emp





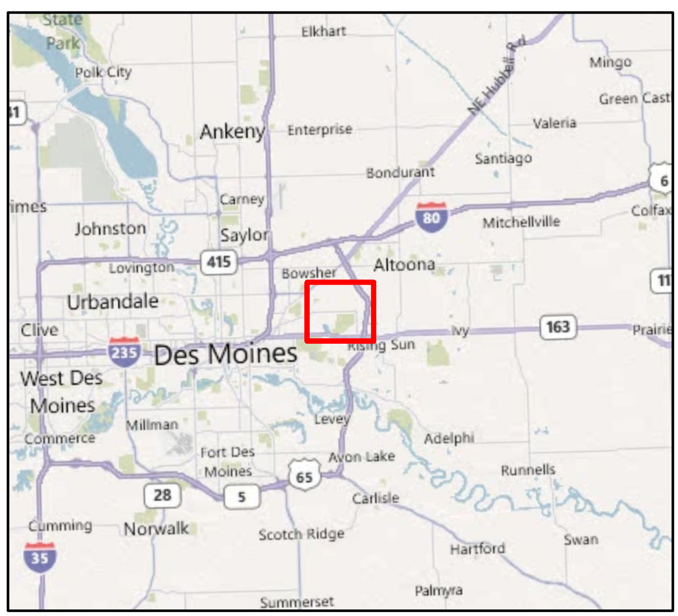
CBG ID: 191530102066

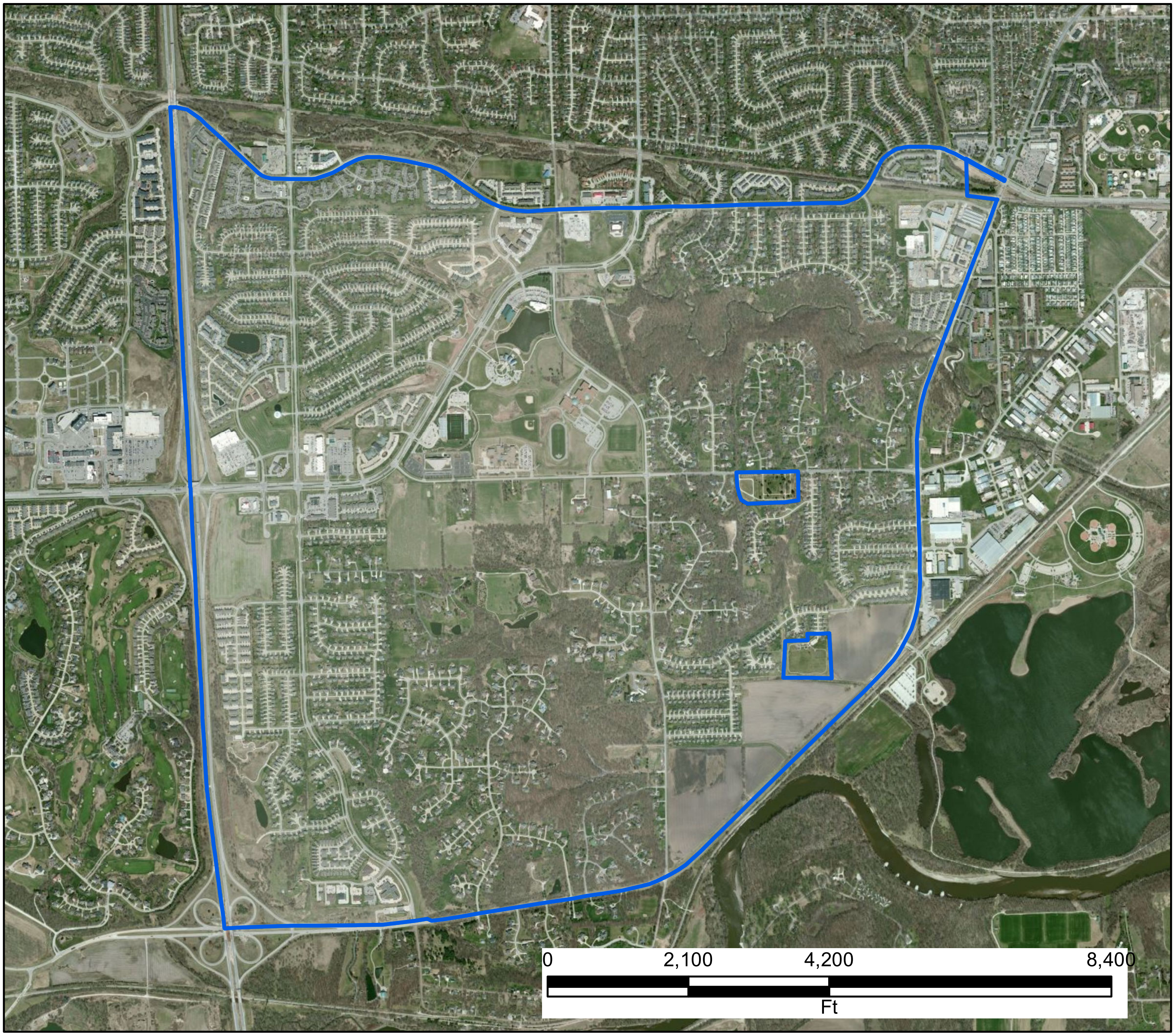
CBG: 191530102066
Des Moines-West Des Moines, IA
Baseline hu/ac: 2.58
Baseline emp/ac: 2.51
D5Ar: 92787
Net ISGr = 0.046 IAC/hu
(2003 ISF/hu)
Net ISGe = 0.035 IAC/emp
(1521 ISF/emp



CBG ID: 191530106007

CBG: 191530106007
Des Moines-West Des Moines, IA
Baseline hu/ac: 0.7
Baseline emp/ac: 0.38
D5Ar: 123787
Net ISGr = 0.082 IAC/hu
(3568 ISF/hu)
Net ISGe = 0.062 IAC/emp
(2708 ISF/emp



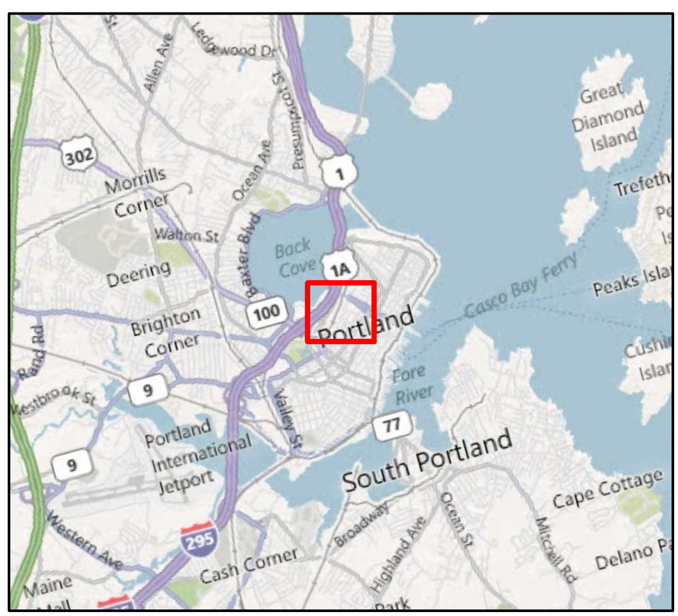


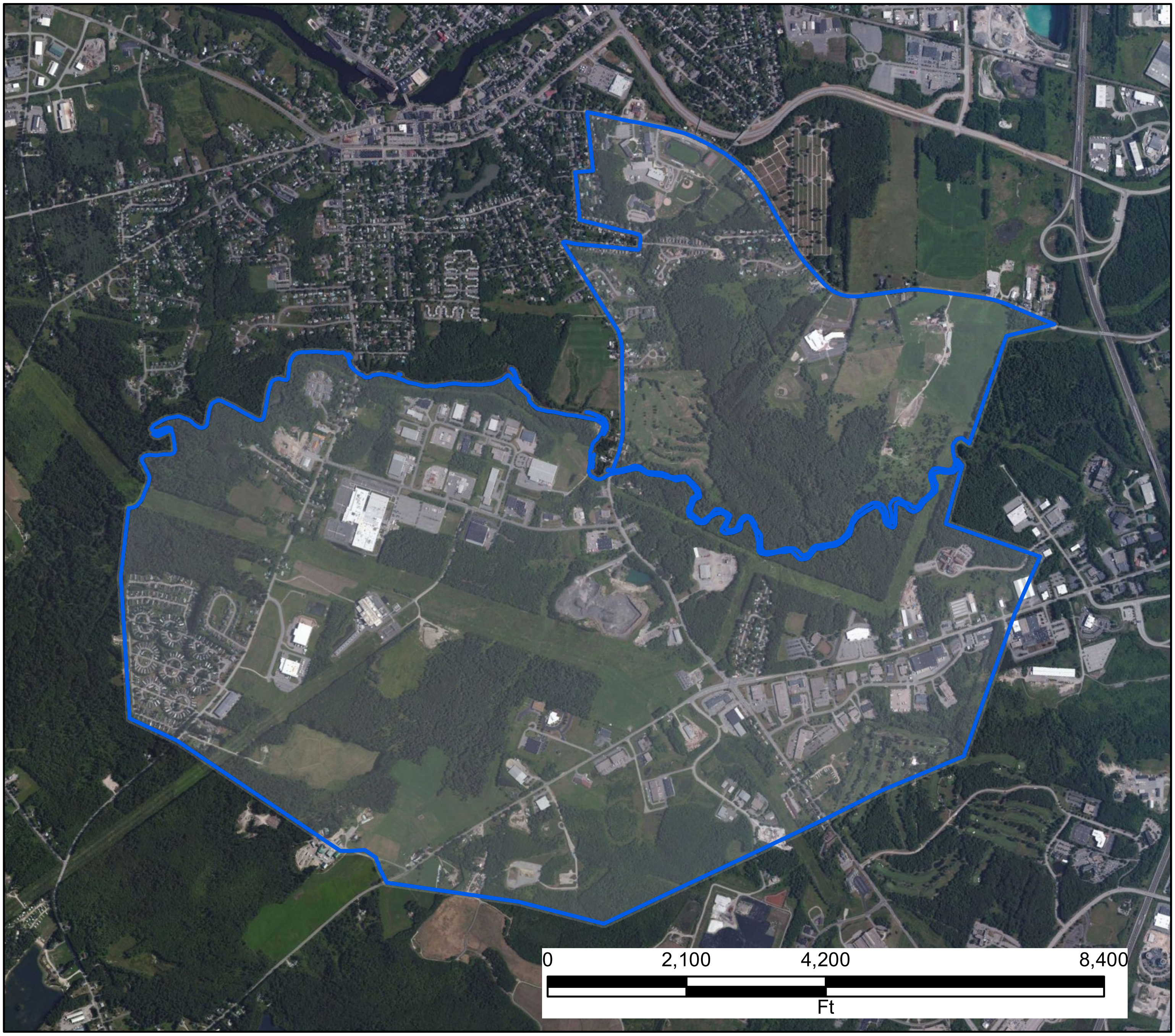
CBG ID: 191530110242

CBG: 191530110242
Des Moines-West Des Moines, IA
Baseline hu/ac: 1.53
Baseline emp/ac: 0.92
D5Ar: 138745
Net ISGr = 0.064 IAC/hu
(2781 ISF/hu)
Net ISGe = 0.048 IAC/emp
(2110 ISF/emp

CBG ID: 230050006002

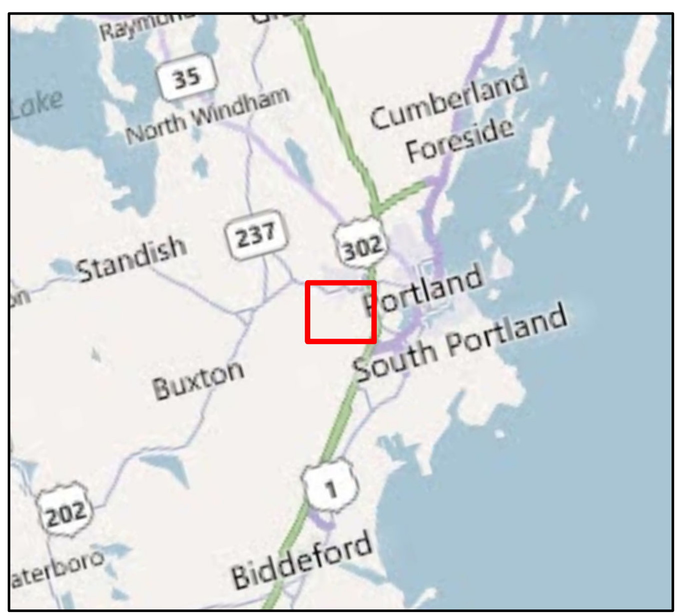
CBG: 230050006002
Portland-South Portland-Biddeford, ME
Baseline hu/ac: 6.08
Baseline emp/ac: 10.9
D5Ar: 107957
Net ISGr = 0.014 IAC/hu
(627 ISF/hu)
Net ISGe = 0.011 IAC/emp
(481 ISF/emp

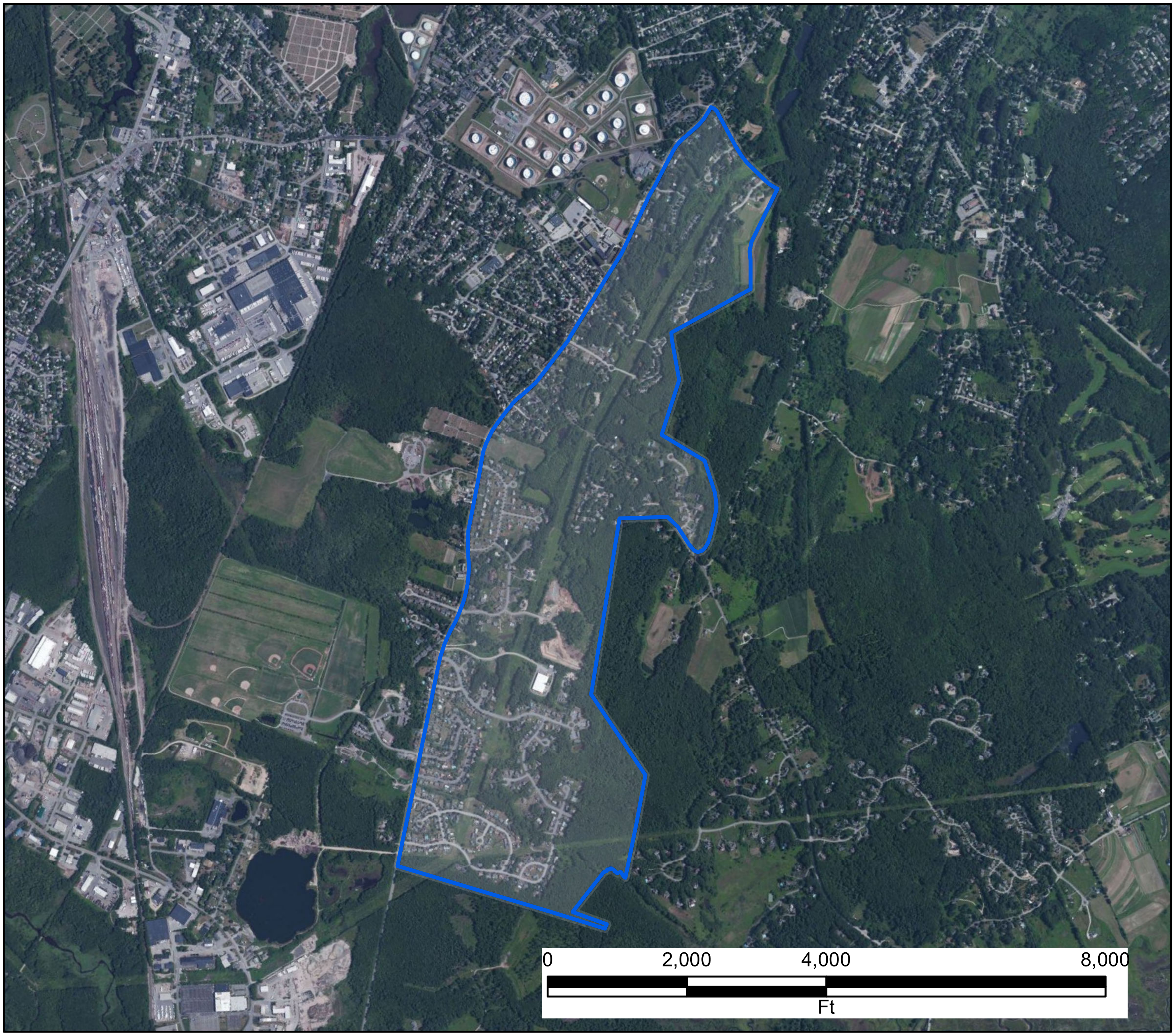




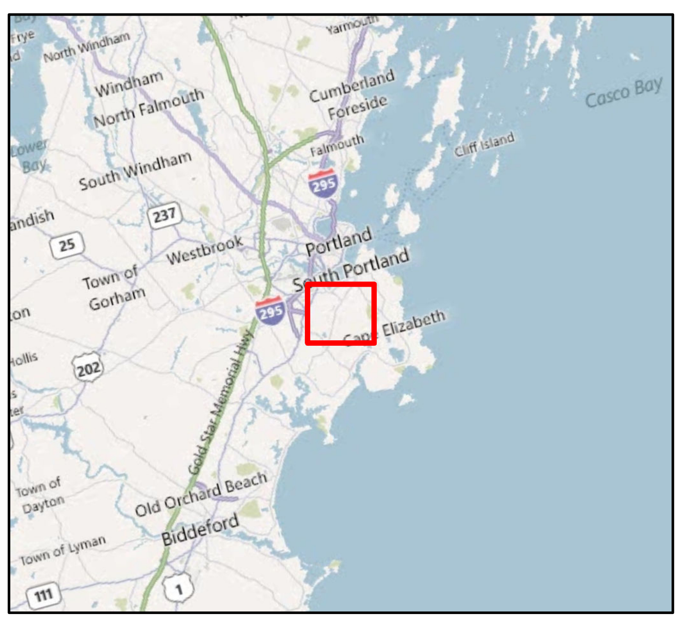
CBG ID: 230050029004

CBG: 230050029004
Portland-South Portland-Biddeford, ME
Baseline hu/ac: 0.4
Baseline emp/ac: 2.33
D5Ar: 84819
Net ISGr = 0.068 IAC/hu
(2983 ISF/hu)
Net ISGe = 0.052 IAC/emp
(2264 ISF/emp

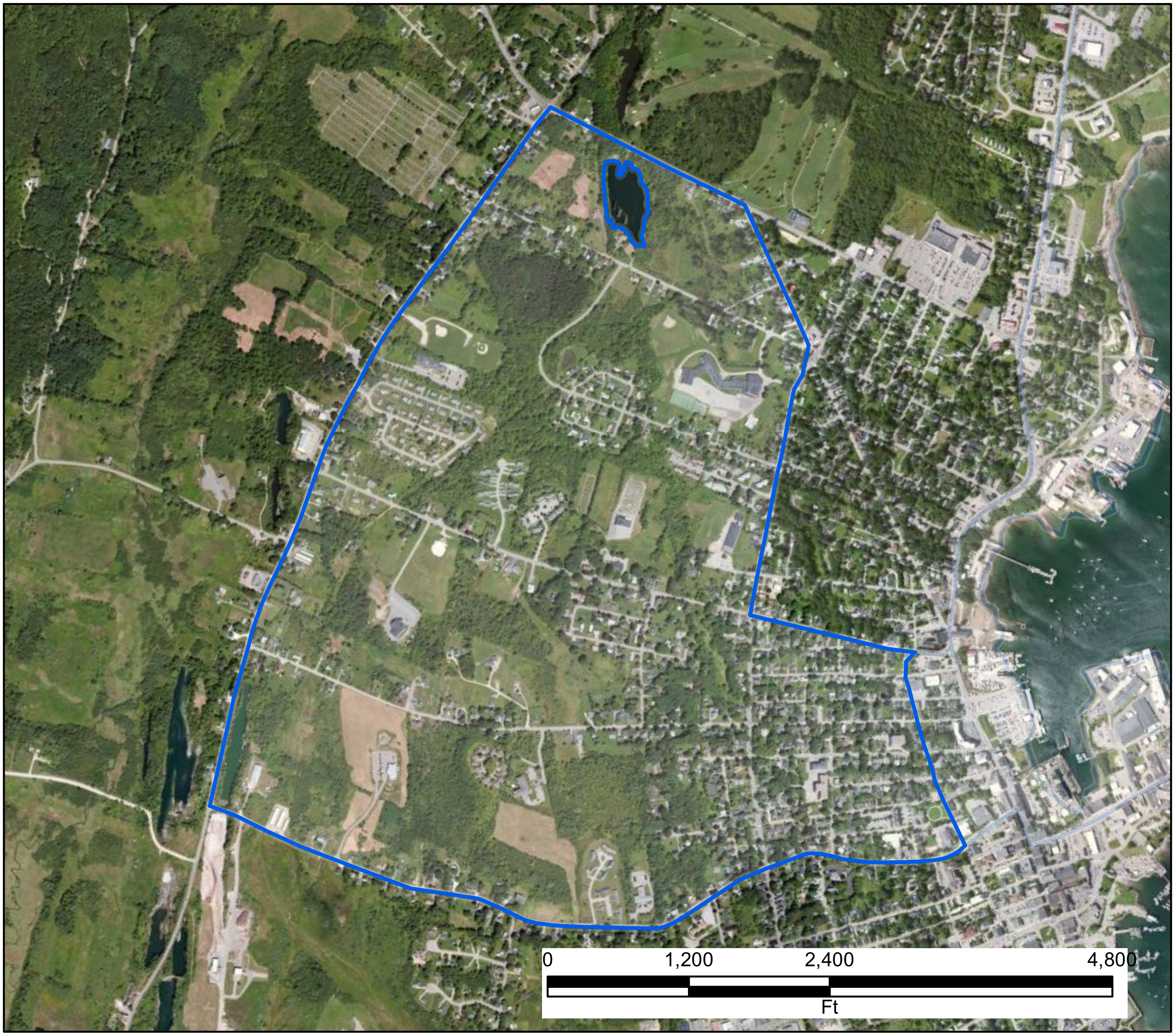




CBG ID: 230050034005

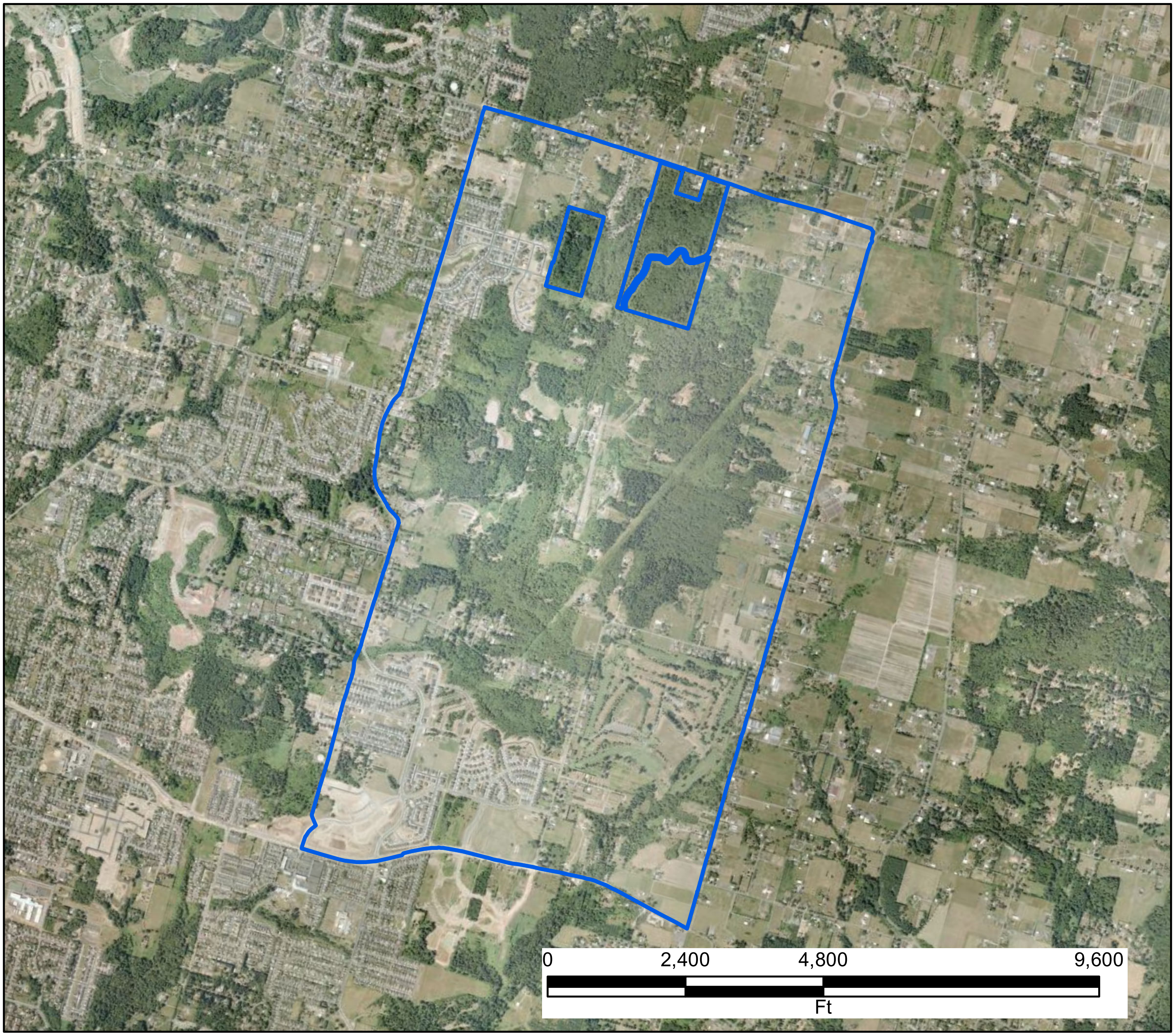


CBG: 230050034005
Portland-South Portland-Biddeford, ME
Baseline hu/ac: 0.77
Baseline emp/ac: 0.1
D5Ar: 98244
Net ISGr = 0.086 IAC/hu
(3747 ISF/hu)
Net ISGe = 0.065 IAC/emp
(2851 ISF/emp



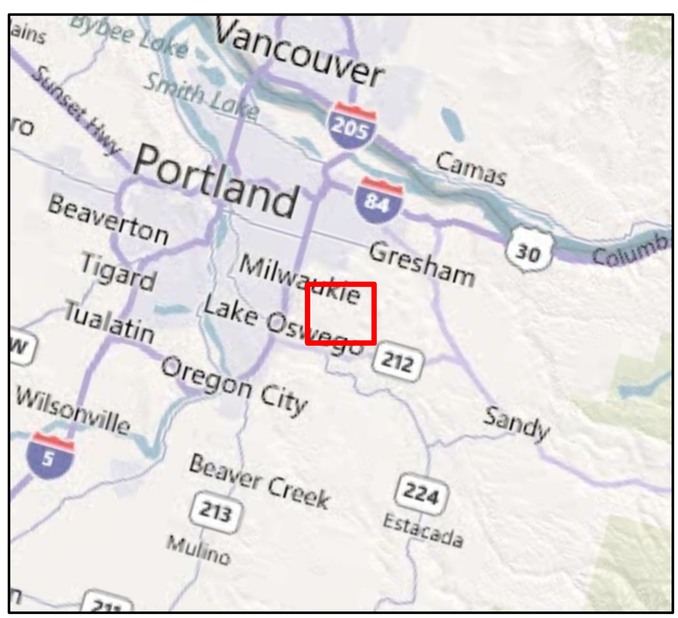
CBG ID: 230139707003

CBG: 230139707003
Rockland, ME
Baseline hu/ac: 1.6
Baseline emp/ac: 0.9
D5Ar: 9456
Net ISGr = 0.072 IAC/hu
(3138 ISF/hu)
Net ISGe = 0.055 IAC/emp
(2387 ISF/emp



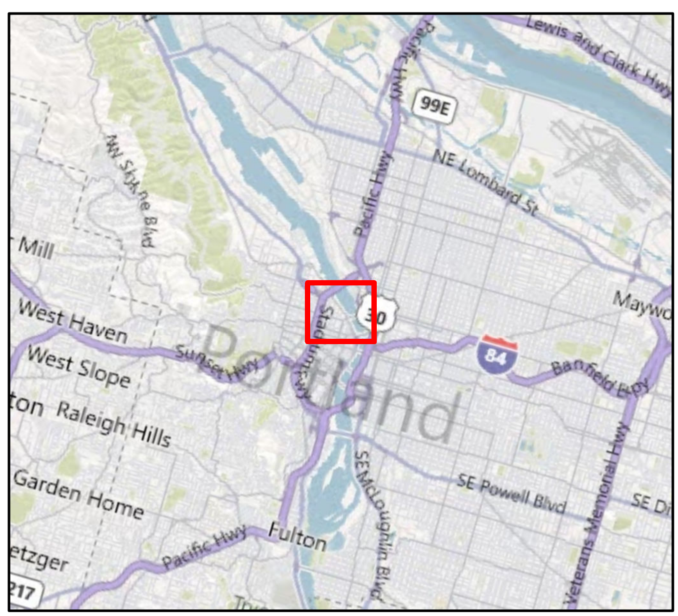
CBG ID: 410050222031

CBG: 410050222031
Portland-Vancouver-Beaverton, OR-WA
Baseline hu/ac: 0.23
Baseline emp/ac: 0.05
D5Ar: 263705
Net ISGr = 0.08 IAC/hu
(3485 ISF/hu)
Net ISGe = 0.061 IAC/emp
(2645 ISF/emp



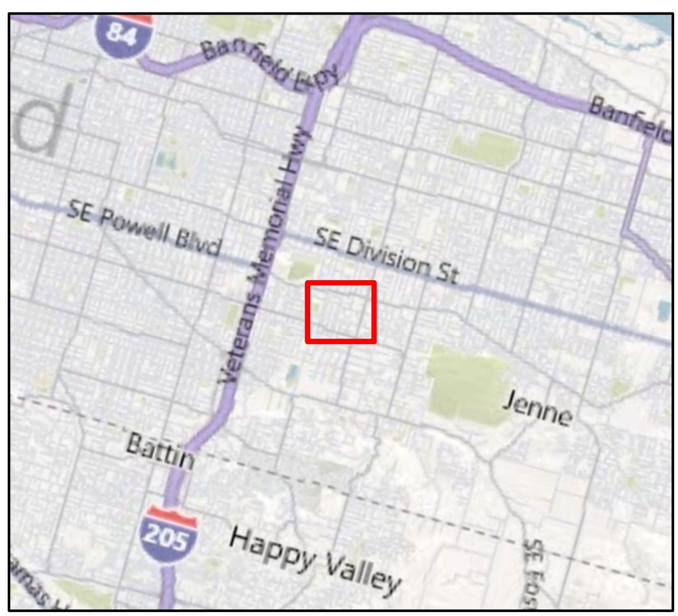
CBG ID: 410510051001

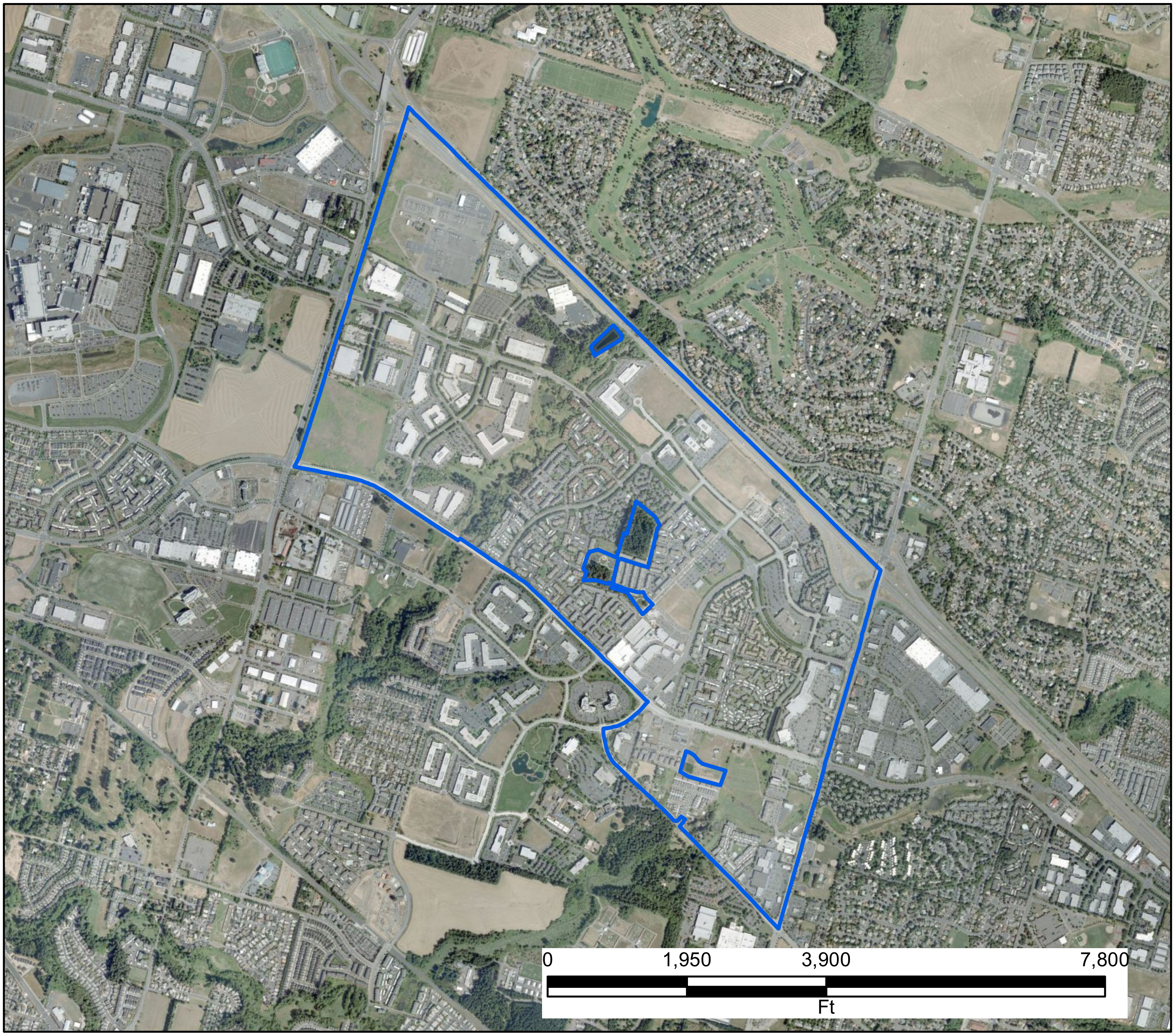
CBG: 410510051001
Portland-Vancouver-Beaverton, OR-WA
Baseline hu/ac: 20.02
Baseline emp/ac: 12.81
D5Ar: 440976
Net ISGr = 0.005 IAC/hu
(212 ISF/hu)
Net ISGe = 0.004 IAC/emp
(161 ISF/emp



CBG ID: 410510084002

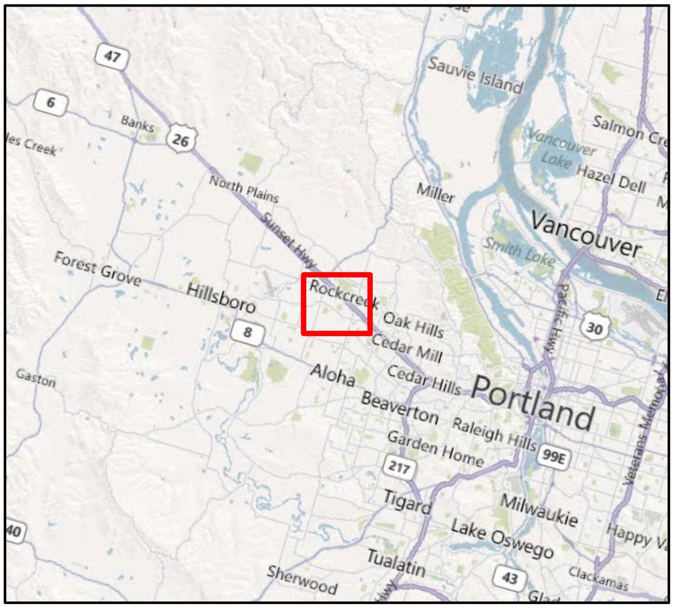
CBG: 410510084002
Portland-Vancouver-Beaverton, OR-WA
Baseline hu/ac: 6.8
Baseline emp/ac: 1.4
D5Ar: 324858
Net ISGr = 0.024 IAC/hu
(1055 ISF/hu)
Net ISGe = 0.019 IAC/emp
(806 ISF/emp

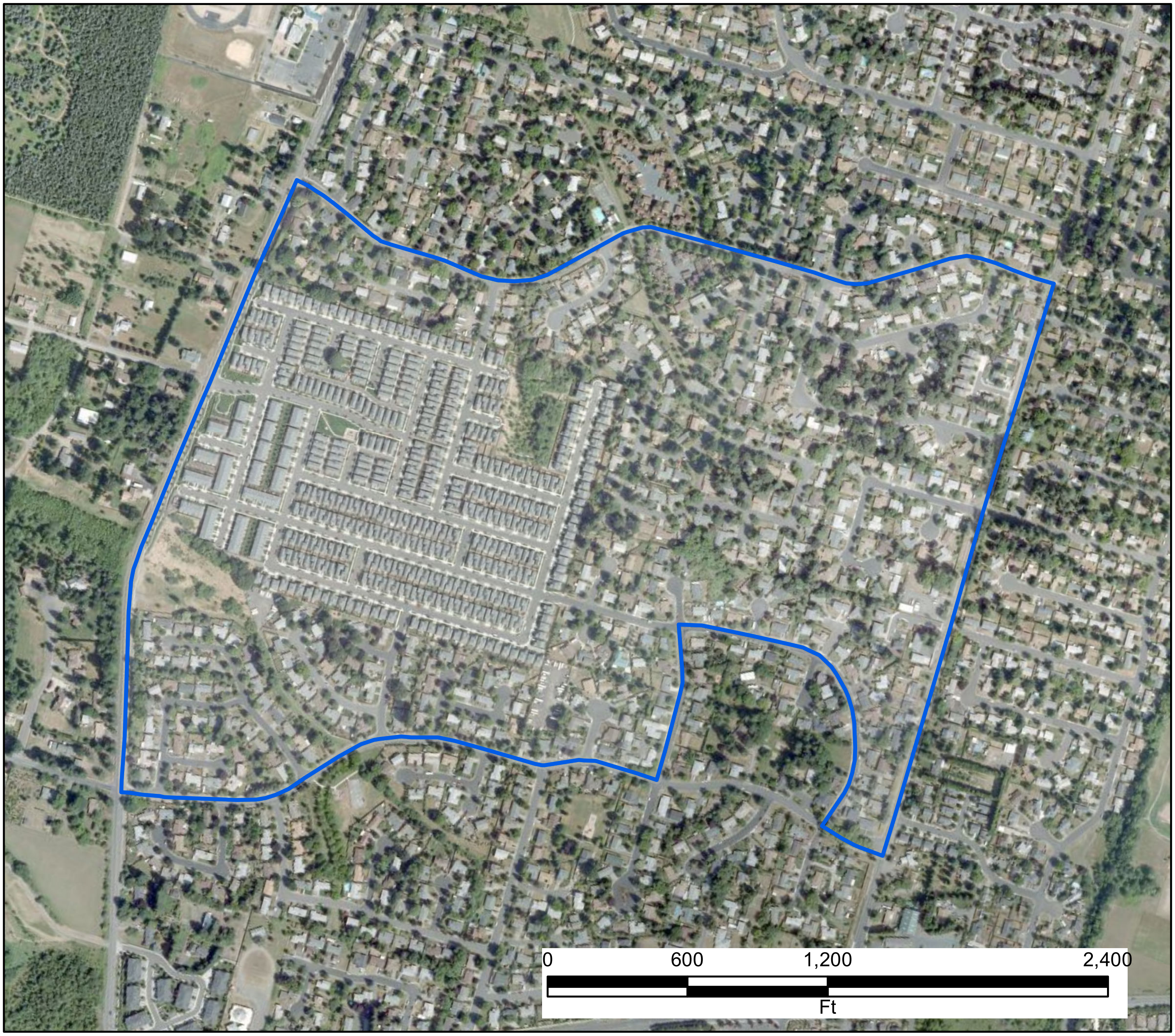




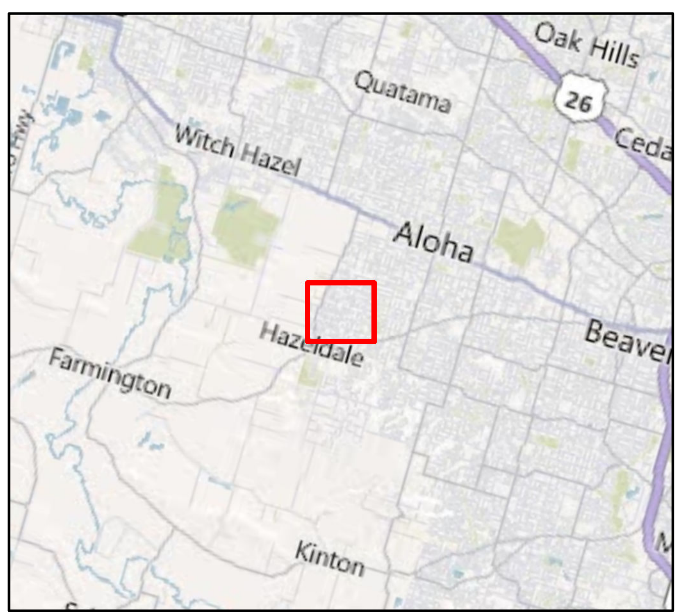
CBG ID: 410670316081

CBG: 410670316081
Portland-Vancouver-Beaverton, OR-WA
Baseline hu/ac: 4.88
Baseline emp/ac: 7.39
D5Ar: 240196
Net ISGr = 0.02 IAC/hu
(869 ISF/hu)
Net ISGe = 0.015 IAC/emp
(660 ISF/emp

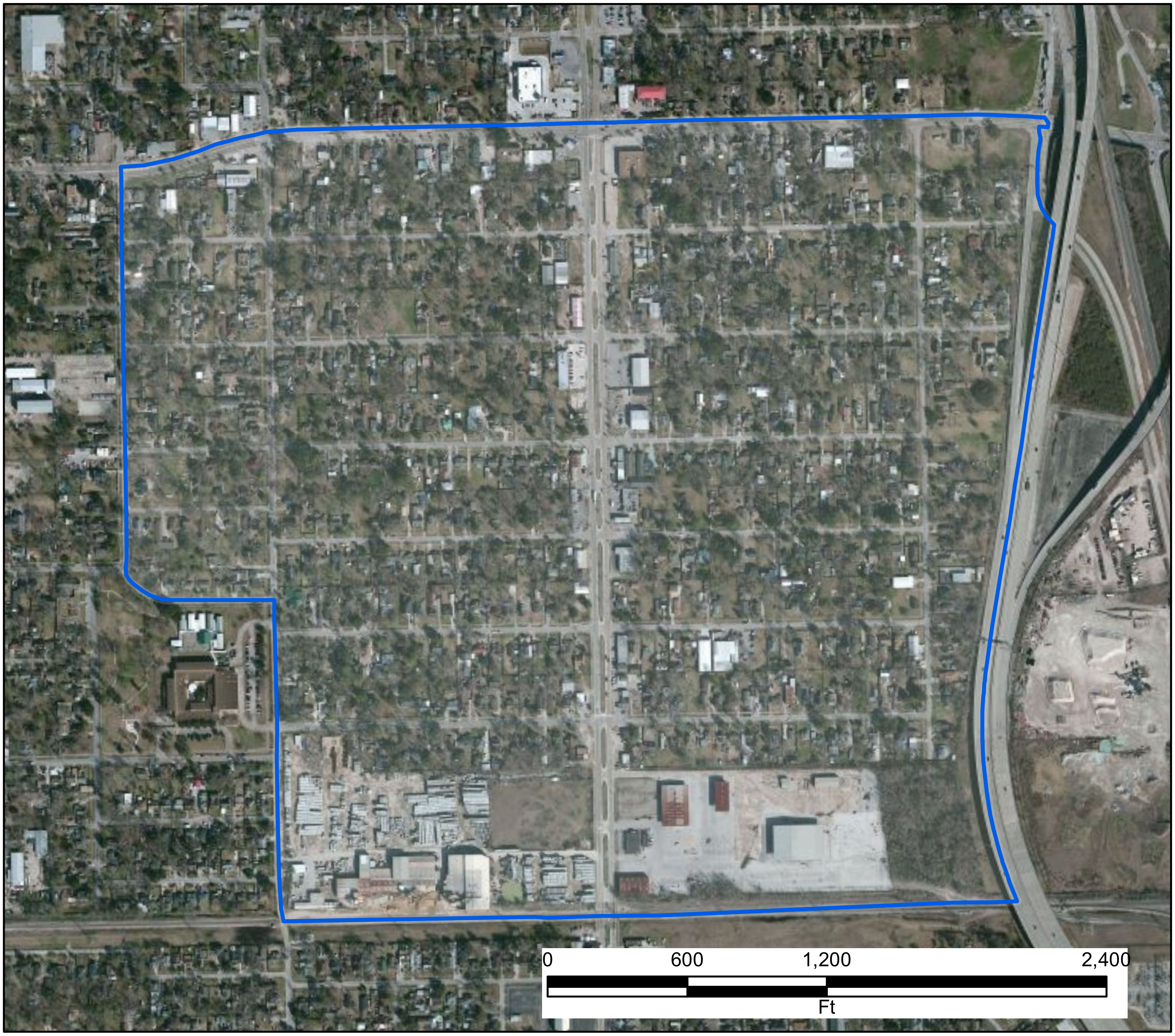




CBG ID: 410670317046

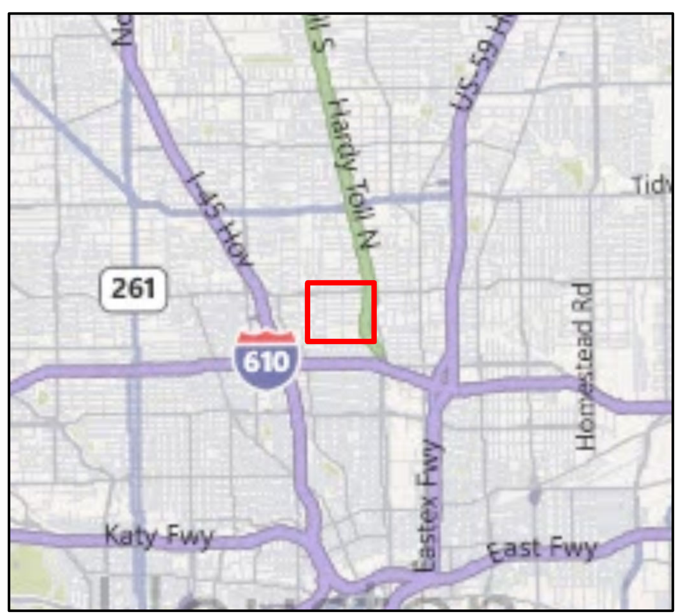


CBG: 410670317046
Portland-Vancouver-Beaverton, OR-WA
Baseline hu/ac: 2.48
Baseline emp/ac: 0.21
D5Ar: 246230
Net ISGr = 0.051 IAC/hu
(2225 ISF/hu)
Net ISGe = 0.039 IAC/emp
(1705 ISF/emp



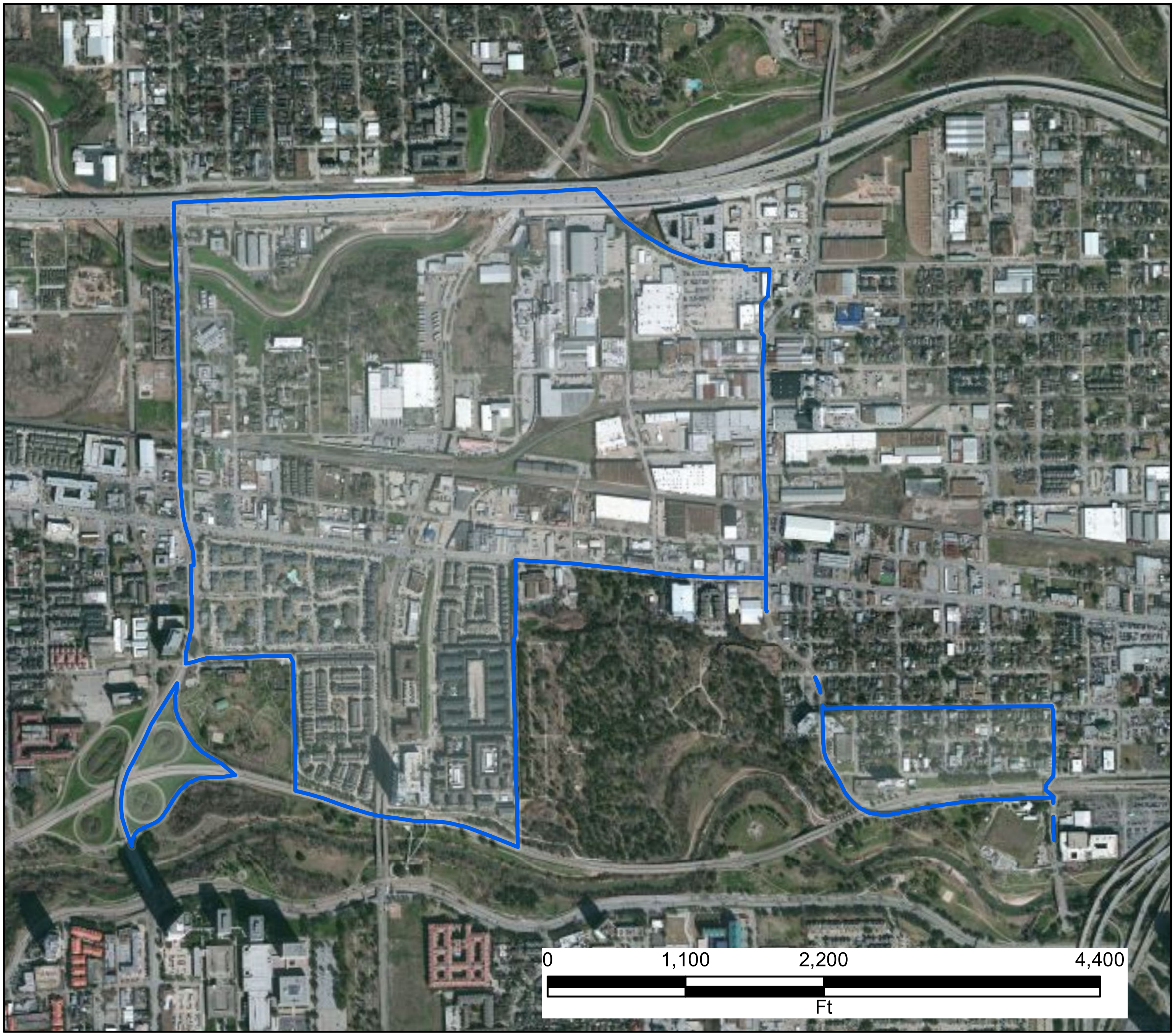
CBG ID: 482012203003

CBG: 482012203003
Houston-Sugar Land-Baytown, TX
Baseline hu/ac: 2.84
Baseline emp/ac: 1.2
D5Ar: 558545
Net ISGr = 0.034 IAC/hu
(1477 ISF/hu)
Net ISGe = 0.026 IAC/emp
(1126 ISF/emp



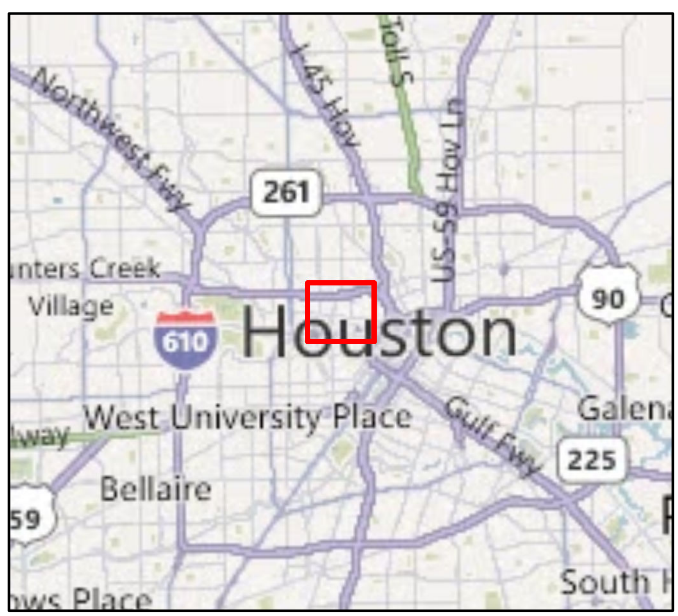
CBG ID: 482013303004

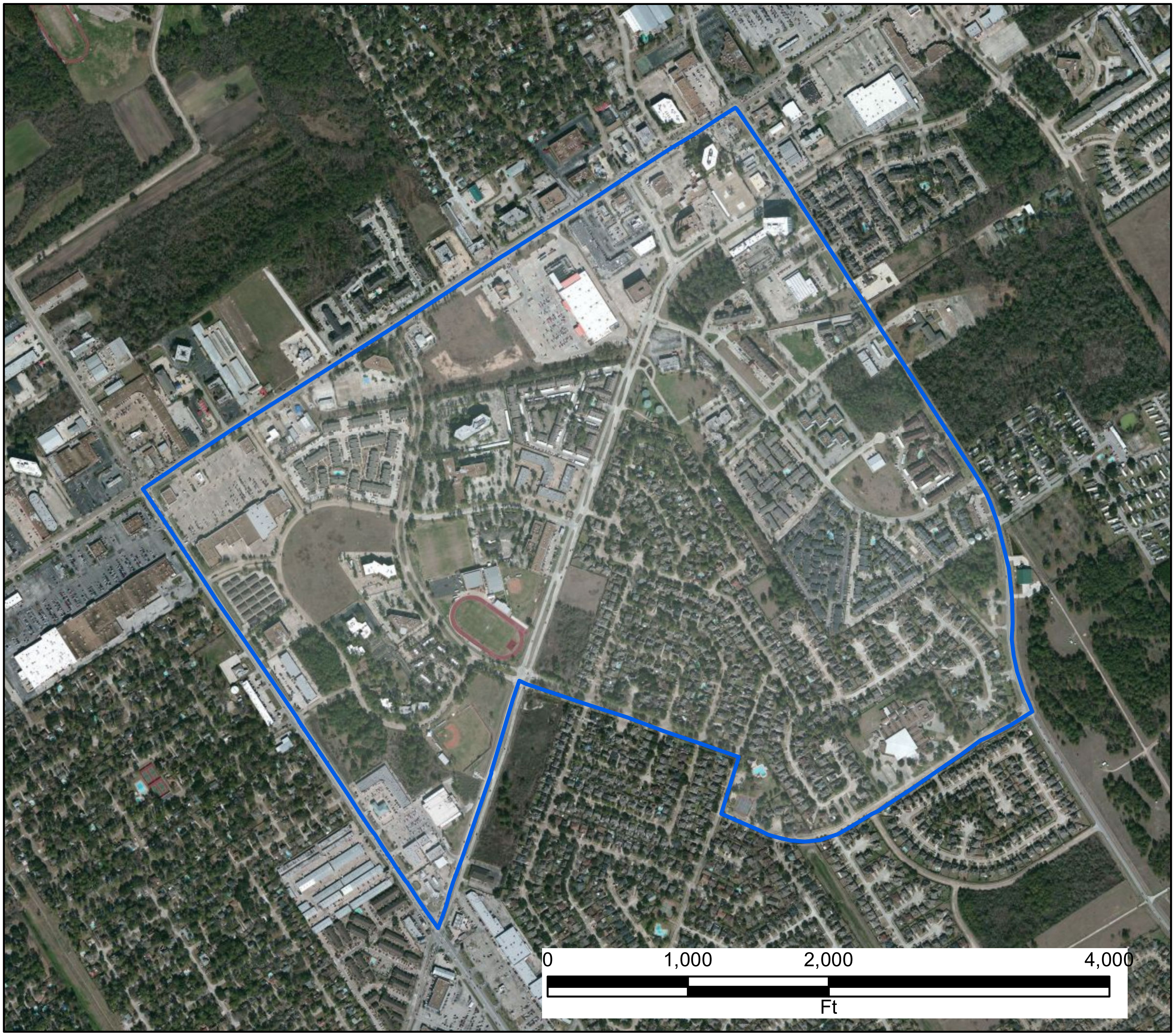
CBG: 482013303004
Houston-Sugar Land-Baytown, TX
Baseline hu/ac: 1.07
Baseline emp/ac: 0.08
D5Ar: 428081
Net ISGr = 0.057 IAC/hu
(2483 ISF/hu)
Net ISGe = 0.043 IAC/emp
(1884 ISF/emp



CBG ID: 482015102002

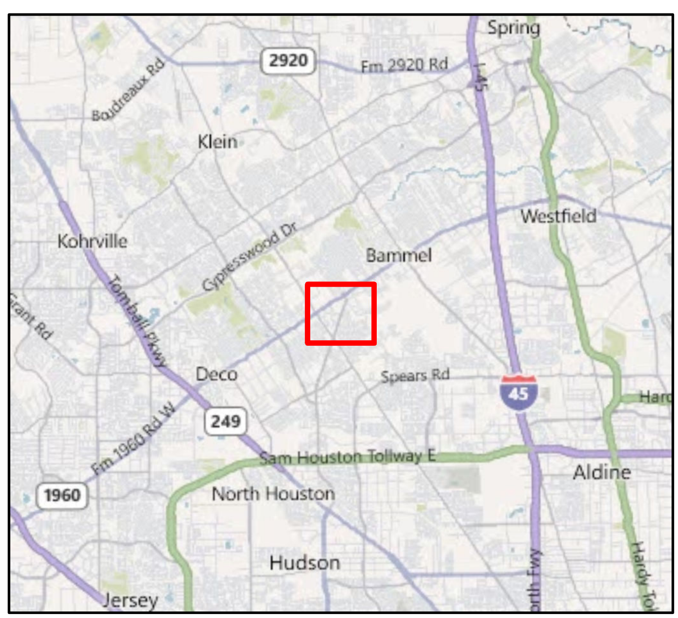
CBG: 482015102002
Houston-Sugar Land-Baytown, TX
Baseline hu/ac: 5.03
Baseline emp/ac: 9.36
D5Ar: 685197
Net ISGr = 0.013 IAC/hu
(588 ISF/hu)
Net ISGe = 0.01 IAC/emp
(447 ISF/emp

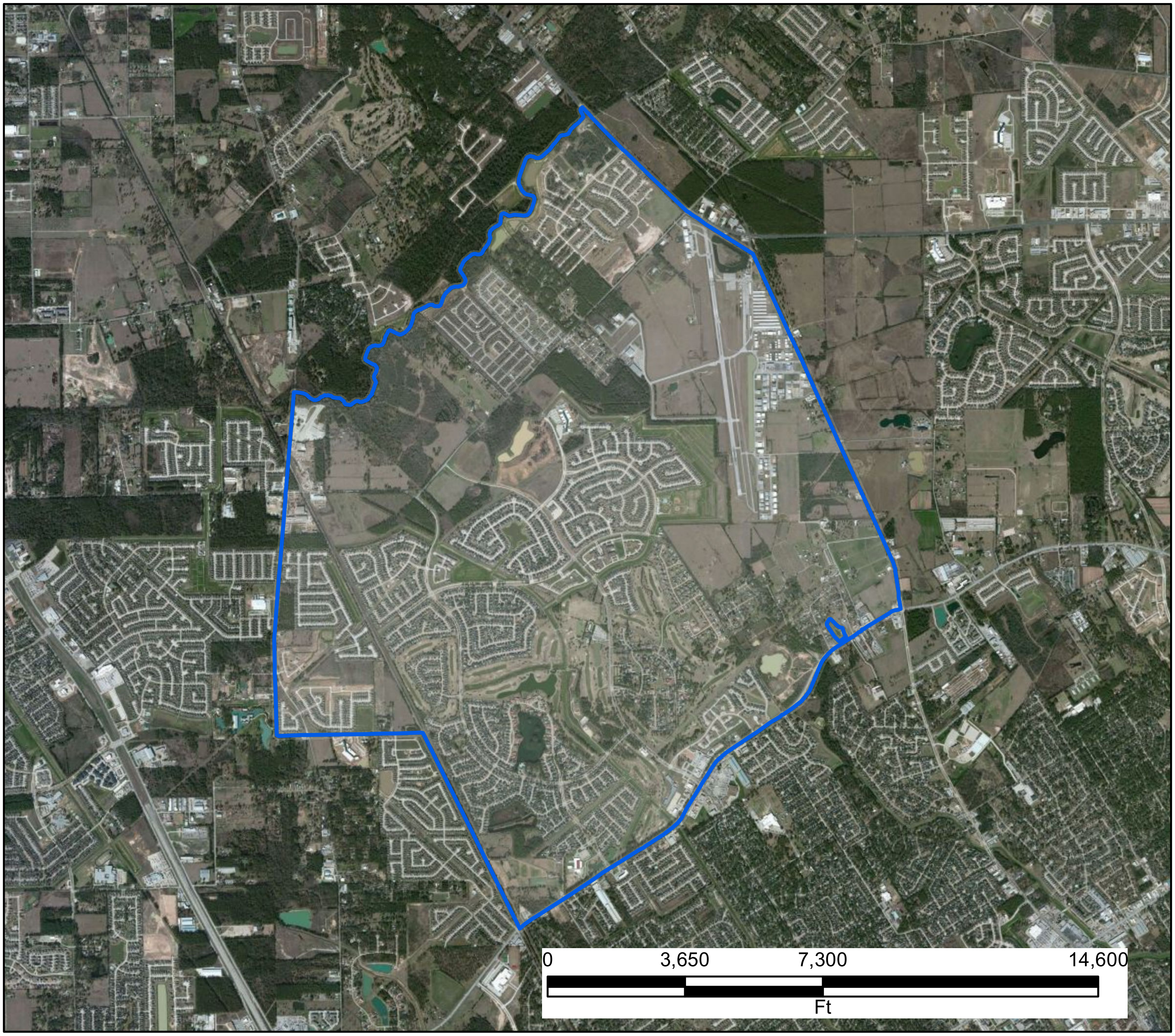




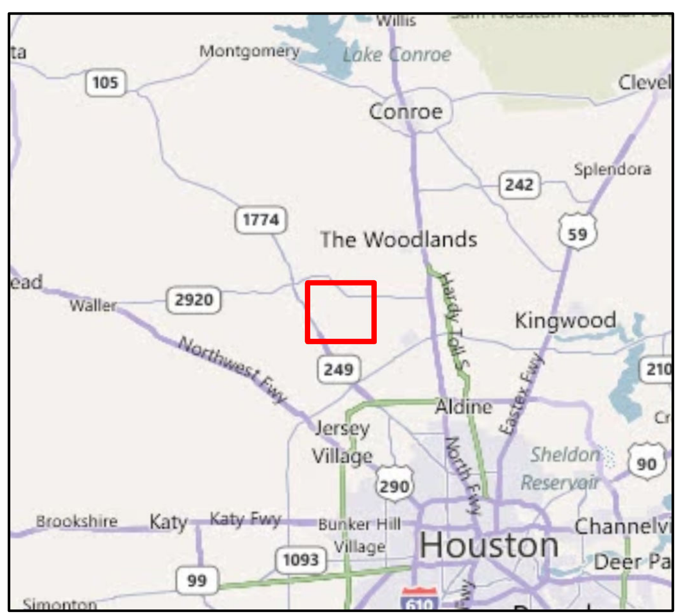
CBG ID: 482015511001

CBG: 482015511001
Houston-Sugar Land-Baytown, TX
Baseline hu/ac: 3.81
Baseline emp/ac: 9.82
D5Ar: 335515
Net ISGr = 0.017 IAC/hu
(761 ISF/hu)
Net ISGe = 0.013 IAC/emp
(578 ISF/emp





CBG ID: 482015548002



CBG: 482015548002
Houston-Sugar Land-Baytown, TX
Baseline hu/ac: 0.39
Baseline emp/ac: 0.28
D5Ar: 196400
Net ISGr = 0.081 IAC/hu
(3544 ISF/hu)
Net ISGe = 0.062 IAC/emp
(2688 ISF/emp