Visualizing Future 3-Dimensional Neighbourhoods in Phoenix: An Application Incorporating Empirical Methods with Computational Graphics

Ariane Middel[1], Subhrajit Guhathakurta[2], Hans Hagen[3], Peter-Scott Olech[4], Florian Höpel[5]

[1]*Department of Computer Science, TU Kaiserslauternm Postfach 3049, 67653 Kaiserslautern (ariane.middel@ariii.com)*

[2]*School of Planning, MailCode 872005, Arizona State University, Tempe, AZ 85287-2005 (subhro.guha@asu.edu)*

[3]*Department of Computer Science, TU Kaiserslautern, Postfach 3049, 67653 Kaiserslautern (Hagen@informatik.uni-kl.de)*

[4]*Department of Computer Science, TU Kaiserslautern, Postfach 3049, 67653 Kaiserslautern (olech@informatik.uni-kl.de)*

[5]*Department of Computer Science, TU Kaiserslautern, Postfach 3049, 67653 Kaiserslautern (f_hoepel@informatik.uni-kl.de)*

Abstract:

Sophisticated simulation models are now extensively used in urban planning for estimating future population and job distributions to measure the impact of planning decisions on future urban environments. Simulated population projections usually result in large, macro-scale, and multivariate geospatial data sets. Millions of records have to be processed, stored, and visualized to help planners explore and analyze complex population patterns. This paper introduces a database driven framework for visualizing geospatial multivariate simulation data from *UrbanSim*, a software-based simulation model for the analysis of future household and building types. The designed framework is extendable and aims at integrating empirical-stochastic methods with multi-dimensional visualization techniques developed for information visualization and cartography.

1. INTRODUCTION

Modelling urban futures has been of considerable interest of late in computer graphics and urban planning. The interest is driven by a number of developments, in particular by increased computing power and significant advances in the field of integrated urban and environmental models [1]. Growing awareness for sustainability amplifies the demand for planning support systems that analyze and visualize future carbon footprints, air quality, traffic volumes, energy intensity, and other indicators. Visualizing critical information about how cities and urban environments might develop in the next one or two decades is an effective tool for analyzing impacts of today's planning decisions on future environments.

Recent efforts in computer graphics aim to automate the complex and expensive task for generating and visualizing realistic cityscapes. Various tools and techniques are constantly being developed for automatically detecting and reconstructing buildings from remotely sensed imagery to generate 3D city models [2] [3] [4] and to undertake building energy calculations [5]. While photogrammetric reconstruction approaches allow for generating existing and past stages of urban developments, they provide little information on future cityscapes. In this context, procedural modelling techniques have been subject to active research lately. Procedural methods algorithmically generate arbitrary geometries from a predefined rule-set. Key techniques for procedural visualization include agent-based modelling approaches [6] and grammar-based approaches [7] [8] [9] [10] [11].

In general, procedural models are suitable for applications where the visualization of look-alike cities is adequate and the empirical validity of the environmental model is less relevant. To date, procedural approaches are not suitable for the visualization of urban simulation data since they lack the capability to model the impacts of human behaviour on urban developments. Furthermore, procedural models digitally create a highly complex visual reality that might impede visual data mining. A realistic representation helps analysts to perceive urban environments in a more tangible way, but at the same time it distracts from the actual task of analyzing and comprehending the underlying complex data structures. The real world is too complex to assimilate at once; therefore we need abstraction to help us interpret it [12]. The specific nature of visualization and cognition is often enhanced through the use of abstract symbols, and not through realistic renderings. Therefore, we propose an integration of abstract and realistic 3D visualization for the visualization of multidimensional urban simulation data.

In this paper, we close the gap between the simulation and visualization of multidimensional geospatial data on future urban environments. First, we present a statistical method for estimating future residential building types on a neighbourhood scale from demographic data. Future building types are crucial for many sustainability metrics, but are not supported by current simulation models. We use multinomial logistic regression (MNL) to map dwelling types derived from household characteristics. We predict building types for the Phoenix metropolitan area based on demographic data from UrbanSim output. Then, we visualize the resulting multidimensional simulation data as abstract symbols on top of Google Earth^{TM}. While several techniques have been explored to generate three-dimensional building objects including procedural or template-based database methods, our research provides an empirical model that allows a visual synthesis of future neighbourhood characteristics in realistic urban contexts.

2. CURRENT VISUALIZATION APPROACHES

Procedural models based on grammars have been developed to generate architecture [7], building facades [8], ancient Roman sites [9], and large-scale 3D cityscapes [10]. Procedural city modelling allows for the generation of realistic-looking urban environments, but to date it lacks underlying empirically-based models to generate meaningful projections of urban growth patterns that can be calibrated to simulate real conditions. However, future population growth and household location is of great interest to urban planners. Planning agencies in most industrialized countries are now mandated to provide official projections on future urban growth to monitor land development. Therefore, geographers and other urban scholars have pursued research in modelling complex urban systems to guide land-use decisions and growth management strategies. Several commercially available GIS-based planning support systems, such as *WhatIf* [13] and *CommunityVIZ* [14] are being widely used in academic and policy contexts. UrbanSim [15] is another open-source planning tool used for analyzing long-term effects of land use and transportation policies on household and job locations. It provides a platform for generating different urban scenarios based on current trends and specified policy choices, such as to examine impacts of low-density urban sprawl or to evaluate the land use implications of transportation plans [16].

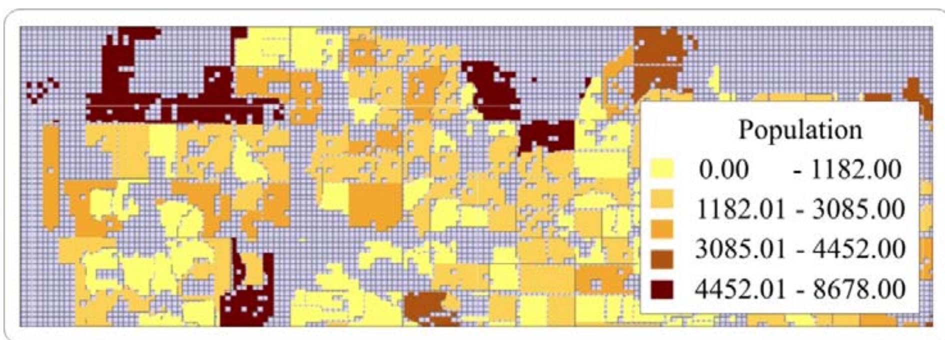

Figure 1: Example of GIS Visualization: Population Density in Phoenix

Typically, projections of urban simulation models are visualized with the help of Geographic Information Systems (GIS) as color-coded polygons or icons on 2D maps (see Fig. 1). Since prediction models usually result in large-scale, highly attributed spatial data sets, the challenge is to find a multidimensional representation for the simulation results. The multi-attributed visualization should enable planners to easily compare different planning scenarios and to evaluate simulated impacts of different land use policies. In the early 70's, Chernoff presented a technique to visualize trends in highly dimensional data by relating data to facial features [17]. Gradually over the years, new information visualization techniques were introduced, ranging from 2D scatterplots to 3D treemaps (see Fig. 2).

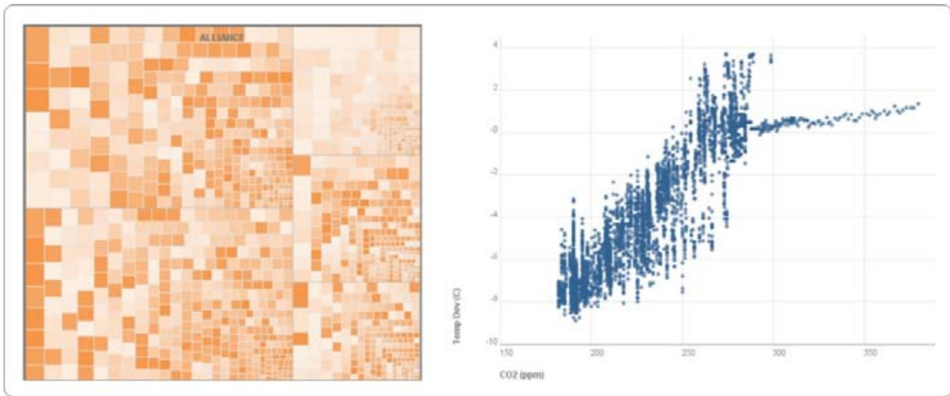

Figure 2: Examples for InfoVIS: Treemap on character data in a World of Warcraft realm, scatterplot comparing CO_2 levels against temperature [18]

Whereas *InfoVIS* primarily deals with the display of large multivariate datasets, cartography is mainly concerned with representations constrained to a spatial domain. The cartographer Bertin established a basis for designing maps in his classical work “Semiology of Graphics" [19] where he identified a set of fundamental visual variables and defined graphical rules for their appropriate use. Since then, Bertin's concepts have been constantly modified and extended. Modern cartography transfers design knowledge from 2D paper maps to new media. On-screen interactive maps are designed to assist in visual data exploration and analyses [20]. Cartographic visualization is also extended to abstract and non-geographic data by spatialization [21].

Recently, efforts have emerged to combine techniques from both cartography and information visualization [22] [23]. Geographic visualization, *GeoVIS*, is a new, rapidly evolving domain, especially since the availability of geodata has increased considerably. In 1998, MacEachren compiled the first research agenda entitled “Visualization - Cartography for the 21st century" [24] and addressed *GeoVIS* research challenges. Since then, cartographic and *InfoVIS* techniques have frequently been applied to design integrated geovisualization tools. Latest advances include multivariate analyses with self-organizing maps [25] [26], studies on human activity patterns using 3D space-time paths, and bivariate maps for public health studies [27]. Most recent activities in geovisualization research are discussed in a paper by M. J. Kraak [28].

Pinnel et al. [29] conducted a study on visualization designs for urban modelling. They found that map-centered visualizations are the most useful portrayals for urban planning and analysis, since map layout encodes location information, which is crucial for decision-making. A map-based visualization approach, “The Indicator Browser", was designed by Schwartzman et al. [30] to display UrbanSim simulation results. The browser uses comparative visualizations of 2D maps to visualize complex multiple variables. This technique is however limited in communicating patterns across many dimensions at a higher geographic resolution.

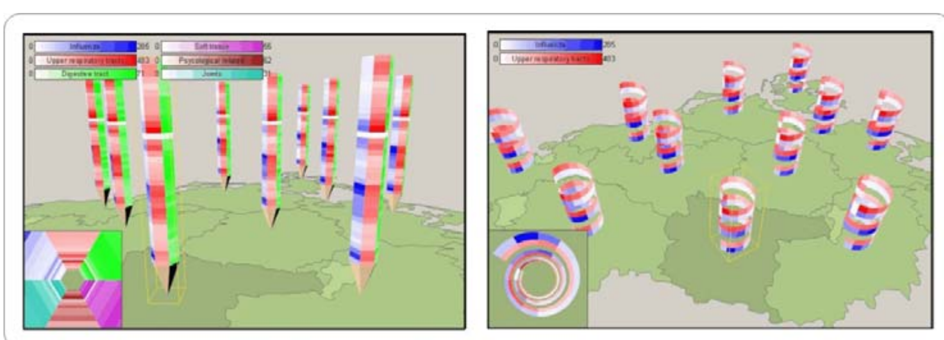

Figure 3: Visualization of monthly health data by means of 3D icons on a map [31]

Instead of encoding *n*-dimensional data in *n* 2D maps, Tominski et al. [31] follow a different approach to display monthly health data (see Fig. 3). They visualized time dependent multivariate disease information as 3D pencil and helix icons geocoded on a base map. This research by Tominski helps to analyze complex patterns across multivariate, spatial, and temporal dimensions, but it lacks a powerful database and GIS functionality to manage, process, and distribute data.

In the following sections, we will present a database-driven simulation and visualization framework that uses abstract visualizations of geospatial data in a 3D context. Within our framework, multidimensional urban simulation data is encoded as specified graphic variables of different geometries and mapped to a Google Earth™ environment to effectively enhance visual thinking. The focus of research here is on designing visualizations applied specifically to the multidimensional simulation data at hand in order to incorporate knowledge into planning processes. We aim at facilitating exploratory visual analyses of simulation data by creating a web-based interactive geovisualization tool.

3. METHODOLOGICAL FRAMEWORK

The framework we use for visualizing future urban neighbourhoods is based on four components: First, the predicted households by type at a fine spatial resolution of 150 meters for Phoenix metropolitan region is obtained with the help of UrbanSim modelling and simulation environment. Second, we estimate the types of buildings that the households will occupy by using logistic regression methods applied to the 2000 Census of Population and Housing. This is achieved by intersecting census block level information with the grid cells layer generated for UrbanSim data. Third, we import the household data and the parameters of the empirical analysis into a PostgreSQL database management system, with the PostGIS module enabled. Finally, Three-dimensional geometries and icons for visualizing the data are developed and implemented in Keyhole Markup Language (KML) for integration with Google Earth™.

3.1 Data modelling with UrbanSim

UrbanSim [15][32] is a modelling environment that uses detailed data on households and employment to predict changes in their locations over time. It consists of several model components simulating different actors in the urban development process, including discrete choice models for household location and relocation, for business choice of employment location, and for developer choices of locations to develop built spaces for various distinct activities. An overview of *UrbanSim* model development as well as a detailed description of implemented model components is given in Borning [33] and Waddell [15]. The open source simulation model was developed by a research group in the University of Washington and is currently implemented in the Digital Phoenix project [34] at Arizona State University to predict jobs and population distribution in the Phoenix Metropolitan area.

3.2 Estimation of residential building types

In order to investigate the effect of household characteristics on discrete types of housing, we use multinomial logistic regression. Building type distributions are based on demographic household information at a Census Block Group scale. To derive homogeneous building categories by location we form clusters with typical building type distributions using k-means techniques in order to establish nominal categories for the regression model. We then model the log odds of the clustered neighbourhood category as a linear function of the household and demographic characteristics of these neighbourhoods. This approach gives good results, but implies a possible correlation between the clustered building type categories. Therefore, we refine our model by estimating building types at grid cell scale. Estimating coefficients for a set of 150m x 150m grid cells with demographic data synthesized from Census [35] gives slightly better results than using synthesized household data. Finally, the estimated coefficients are applied to UrbanSim simulation output to derive predicted building types from household location.

3.3 Data management with PostgreSQL and PostGIS

PostgreSQL [36] is an open source object-relational database management system (ORDBMS). In contrast to relational database management systems, an ORDBMS is not limited to a pre-defined set of data types, which raises the level of abstraction. PostgreSQL natively supports i.a. arbitrary precision numerics, unlimited length text, arrays, and geometric primitives. In addition, it provides support for the integration of custom data types and methods into the database.

As geospatial extension to the PostgreSQL backend server, we use the PostGIS module [37]. PostGIS is an open source add-on developed by Refractions Research under the GNU General Public License and enables PostgreSQL to integrate spatial data structures into the database. PostGIS follows the Simple Features for SQL specification (SFS) from the Open Geospatial Consortium (OGC). The OGC is an international non-profit organization that is leading the development of standards for geospatial and location based services [38]. As a Simple Features for SQL compliant spatial database, PostGIS includes the geometry types diagrammed in Figure 5 and provides functionality for spatially enabled SQL queries like distance between geographic objects, unions, calculation of perimeter, and buffering.

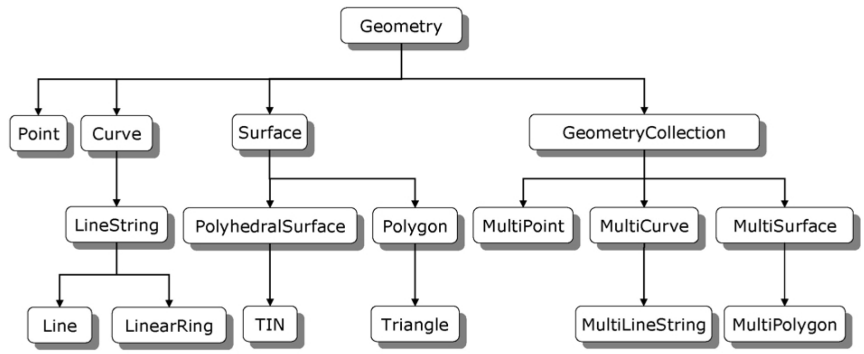

Figure 4: OGC Simple Feature Specification [38]

3.4 Data visualization with Google Earth™

Created by Keyhole Inc. and originally named Earth Viewer, Google Earth™ (GE) [39] maps the earth by superimposing satellite images and aerial photos on a virtual globe. GE allows the user to interactively browse the globe in 3D view and to zoom from space into street level views. Data is streamed from Google's Server upon request to the client computer. To date, most parts of the earth's surface are covered with images having a minimum resolution of 15 meters and a maximum age of 3 years. The aerial photographs are mapped onto a digital elevation model (DEM) provided by NASA. Google Earth™ uses a map projection called General Perspective to show the earth as it appears from space. This cartographic projection resembles an orthographic projection, but instead of an infinite point of perspective it has a finite point of perspective near the globe.

Google Earth™ has the capability to combine the multi-resolution raster image representation of the planet with any kind of georeferenced data. The geobrowser allows overlaying a wide set of geographic features like streets, freeways, and county borders. The user can filter those data sets by space, time, and layer. Furthermore, Google Earth™ supports an overlay of points of interests, placemarks as well as 3D buildings and structures onto the surface. Layers containing geospatial data are managed through KML.

4. RESULTS

This section reports the results of our estimation procedure for deriving building types from UrbanSim output and the implementation of the visualization engine using PostgreSQL and KML. UrbanSim baseline data on households is obtained from the Digital Phoenix project that has implemented UrbanSim for Maricopa County at both 1 mile and 150 meter resolutions. The households data for UrbanSim contain detailed information about each household in Maricopa County including the number of people, number of workers, number of children, racial and ethnic characteristics of head of household, income, and the number of cars. This data is synthesized from the 2000 Census of Population and Housing and 5 percent Public Use Microdata Samples (PUMS) using the household synthesizer provided as part of UrbanSim.

We derive the building types from the Maricopa County Assessors data for 2000, which is an extensive database providing detailed property information at the parcel level. The Assessor's parcel date file is intersected with the Census data at the grid cell level with the help of ArcGIS™ for generating shapefiles. The Primary Use Codes in the Assessor's data provide an effective classification system and a filter. We use this code for defining single-family dwellings and apartments that form the two main residential building type categories in our analysis.

The single-family category is sub classified into lots with different sizes, the apartments are subdivided according to the number of housing units. Altogether, we obtain four different building type categories:

1 = single family, small lots
2 = single family, medium lots
3 = single family, large lots
4 = apartments

Figures 6 to 8 show aerial photographs of representative building types in the Phoenix metropolitan area.

Figure 5: Single family dwellings, small lots

Figure 6: Single family dwellings, medium lots (a) and large lots (b)

Figure 7: Apartments

4.1 Results of Multinomial Regression of household characteristics on building types

In our multinomial regression model for Maricopa County, we assign a dominant building type to each grid cell by identifying the dwelling type with most frequency counts normalized by all residential units in the grid cell.

		N	Marginal Percentage
Category	1	6,339	18.6%
	2	3,872	11.4%
	3	22,704	66.8%
	4	1,098	3.2%
Total		34,013	100.0%

Table 1: Case Processing Summary

Table 1 shows the number of grid cells for each building type, summing up to a total of 34,013 grid cells. The explanatory variables for our regression model are demographic household characteristics from Census. In order to parse Census data down to the level of grid cells, we intersect the Maricopa County block group shape file with the UrbanSim grid cell file and assign Census demographics to each household in the corresponding grid cell.

Cox and Snell	0.523
Nagelkerke	0.617
McFadden	0.393

Table 2: Pseudo R^2

Regression output table 2 shows three pseudo R^2 estimates: Cox and Snell R^2, Nagelkerke's R^2, and McFadden's R^2. Larger values between 0 and 1 indicate a better explanation of the variation by the model, which means that our model performs reasonably well.

		Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	64,020.221			
Final	38,864.008	25,156.213	24	0.000

Table 3: Model fitting information

The test statistic -2LL confirms the significance of the overall logistic regression model at a rounded 0.000 level (compare table 3) and suggests that our model is well fitting. A Likelihood ratio test of individual model parameters reveals that all independent variables are linearly related to the log odds of the dependent variable also at a very high significance level (see table 4).

		Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	39,071.004	206.996	3	0.000
Population Density	50,861.503	11,997.495	3	0.000
Median Household Income	39,506.340	642.332	3	0.000
Minorities (%)	39,534.047	670.040	3	0.000
Hispanics (%)	39,093.025	229.017	3	0.000
Average Household Size	39,062.419	198.411	3	0.000
Distance to Highway	39,391.503	527.495	3	0.000
Children per Household	38,967.626	103.618	3	0.000
Cars per Household	38,987.171	123.164	3	0.000

Table 4: Likelihood ratio statistics, reduced model

A comparison of observed and predicted frequency values as displayed in table 5 strongly supports the reasonably high predictive efficiency of the model. In general, single family dwellings (1, 2, 3) are rarely estimated as apartments (4), whereas apartments are mixed up with single family buildings on a small lot in about 50% of the cases. A possible explanation for this confusion might be a high similarity between incorporated demographic characteristics of households choosing to live in apartments and households living in small single-family dwellings.

Observed	Predicted				
	1	2	3	4	Percent Correct
1	3,924	240	2,100	75	61.9%
2	1,451	457	1,960	4	11.8%
3	700	43	21,961	0	96.7%
4	548	7	37	506	46.1%
Overall Percentage	19.5%	2.2%	76.6%	1.7%	78.9%

Table 5: Classification table

A complete listing of model parameters for the multinomial logistic regression is summarized in table 6. The estimated coefficients reflect the effect of our demographic variables on the likelihood of households living in an apartment (reference category 4) relative to living in a single family dwelling (categories 1-3). In general, a positive sign of the coefficients indicates increased likelihood while a negative sign reduces the choice probability of the corresponding building type.

The explanatory variable population density has an overall negative effect. As population density decreases the likelihood of single-family dwellings with respect to apartments becomes higher. The fact that an increase in population density lowers the likelihood of single-family buildings is obvious, since building types are inherently related to population and housing density. The impact of the discussed explanatory variable is confirmed by the high significance of the corresponding coefficients.

The variables income and distance to highway have a positive effect but is smaller than 10^{-4}. Nevertheless, income is highly significant for the estimation at a 0.000 level whereas distance to highway lacks significance for most of the outcome categories.

The percentage of minorities has a negative effect on the model, suggesting that increasing proportion of minorities decreases the odds that the corresponding grid cells will include mostly single-family buildings. Findings also indicate that the demographic variable Hispanics has a slight positive effect on all associated alternatives.

The effect's algebraic sign of the average number of children varies within single family building type categories. Furthermore, the explanatory variable children does not appear to be significant at all for choosing building type category 2 over apartments. A relatively large corresponding standard error indicates a lower precision with which the parameters are estimated.

Finally, we find the average number of cars and the average household size is important for building type prediction. Negative parameter estimates are associated with the variable cars in categories 1-3 whereas household size exerts a significant positive effect on the model.

In summary, the high significance of the demographic explanatory variables in our model indicates their importance as determinants of building type choice. Population density is an especially important parameter for predicting different dwelling types.

			Std. Error	df	Sig.	Exp( )
1	Intercept	1.196	0.177	1	0.0000	
	Population Density	-0.076	0.003	1	0.0000	0.927
	Median Household Income	0.000	0.000	1	0.0000	1.000
	Minorities (%)	-0.057	0.005	1	0.0000	0.945
	Hispanics (%)	0.030	0.007	1	0.0000	1.031
	Average Household Size	1.098	0.161	1	0.0000	2.999
	Distance to Highway	0.000	0.000	1	0.8894	1.000
	Children per Household	0.737	0.284	1	0.0095	2.089
	Cars per Household	-0.851	0.174	1	0.0000	0.427
2	Intercept	0.696	0.205	1	0.0007	
	Population Density	-0.114	0.003	1	0.0000	0.893
	Median Household Income	0.000	0.000	1	0.0000	1.000
	Minorities (%)	-0.079	0.007	1	0.0000	0.924
	Hispanics (%)	0.010	0.008	1	0.2558	1.010
	Average Household Size	2.165	0.176	1	0.0000	8.716
	Distance to Highway	0.000	0.000	1	0.9292	1.000
	Children per Household	-0.038	0.311	1	0.9037	0.963
	Cars per Household	-1.694	0.187	1	0.0000	0.184
3	Intercept	2.354	0.187	1	0.0000	
	Population Density	-0.283	0.004	1	0.0000	0.754
	Median Household Income	0.000	0.000	1	0.0000	1.000
	Minorities (%)	-0.158	0.007	1	0.0000	0.854
	Hispanics (%)	0.095	0.008	1	0.0000	1.100
	Average Household Size	1.650	0.171	1	0.0000	5.205
	Distance to Highway	0.000	0.000	1	0.0000	1.000
	Children per Household	1.567	0.303	1	0.0000	4.792
	Cars per Household	-1.272	0.188	1	0.0000	0.280

Table 6: Estimated Coefficients

The final model's predictive accuracy is reasonably good for all outcome categories, although the model has some weakness in distinguishing apartments from single family dwellings with small lots. Future research will be dedicated to finding variables that help differentiating between these categories. Moreover, further work is necessary to refine dwelling type categories. Additional building attributes should be taken into account, such as, the number of floors. At the time of our analysis, the number of floors was not available in parcel level data.

4.2 Geometry generation and visualization

We use PostgreSQL geodatabase as a basis for multidimensional information visualization. UrbanSim input and output data and estimated building types are stored in this database and encoded in scalable 3D geometries. This is then visualized in a geospatial context on top of Google Earth^{TM}. Geometric objects are created for every grid cell from geometric primitives. Geometry calculations are performed within PHP scripts. For each record in the geodatabase, modular scripts select the associated attributes to be visualized and generate user-specified geometries. At the same time, size and shape of the geometries are scaled according to attribute values.

The final visualization component of this project was accomplished by incorporating KML to display 3-dimensional geometries draped over the terrain visible in Google Earth^{TM}. First, the 150m x 150m grid from UrbanSim was imported as layer into Google Earth^{TM}. Second, 3-dimensional geometries were developed for the estimated four building types. Third, three ranges of transparencies were applied to the building types to represent that probability of predicting the correct building type based on our empirical estimates. Fourth, five different density classes were established, which could then be visualized by scaling the building footprint in relation to expected density. Finally, a classification system was established to visualize other demographic attributes like access, population share, average number of cars, average number of children, and average income.

We provide four screenshots as examples of the flexible and interactive geometry layers designed to work in conjunction with Google Earth™. Figure 10 shows building types and densities together with average income in the grid cell. Figure 11 shows the distance to nearest highway as color-coded grid cells. Figure 12 displays a close-up of different building types, iconized as dwellings and distinguishable by different roof shapes.

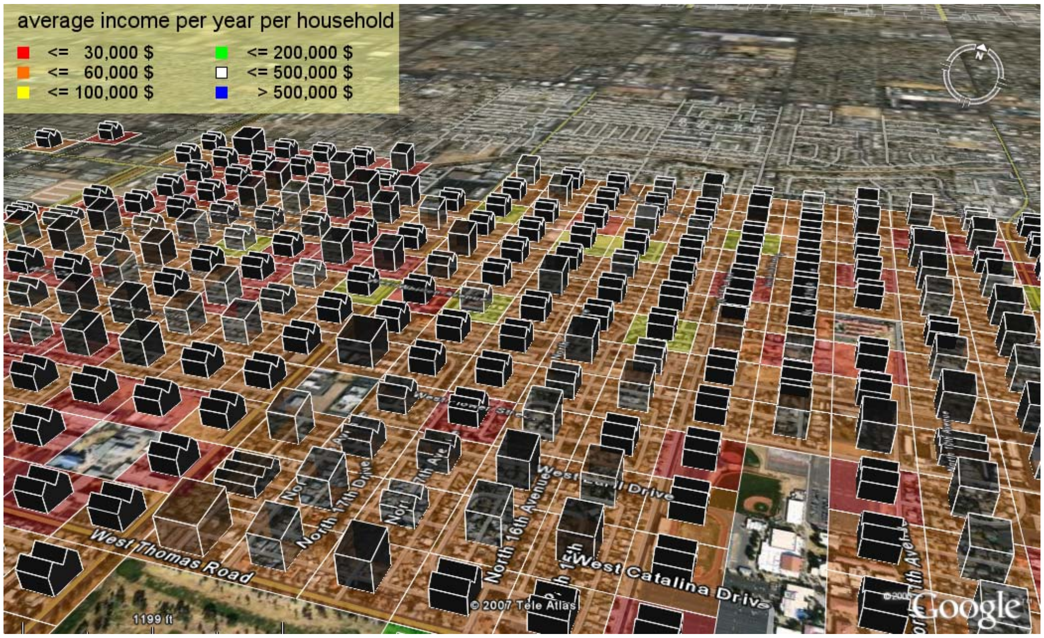

Figure 8: Visualization of (a) average income (color-coded grid cells), (b) building types (geometry), (c) population density (size of footprint), and (d) uncertainty of building type prediction (transparency)

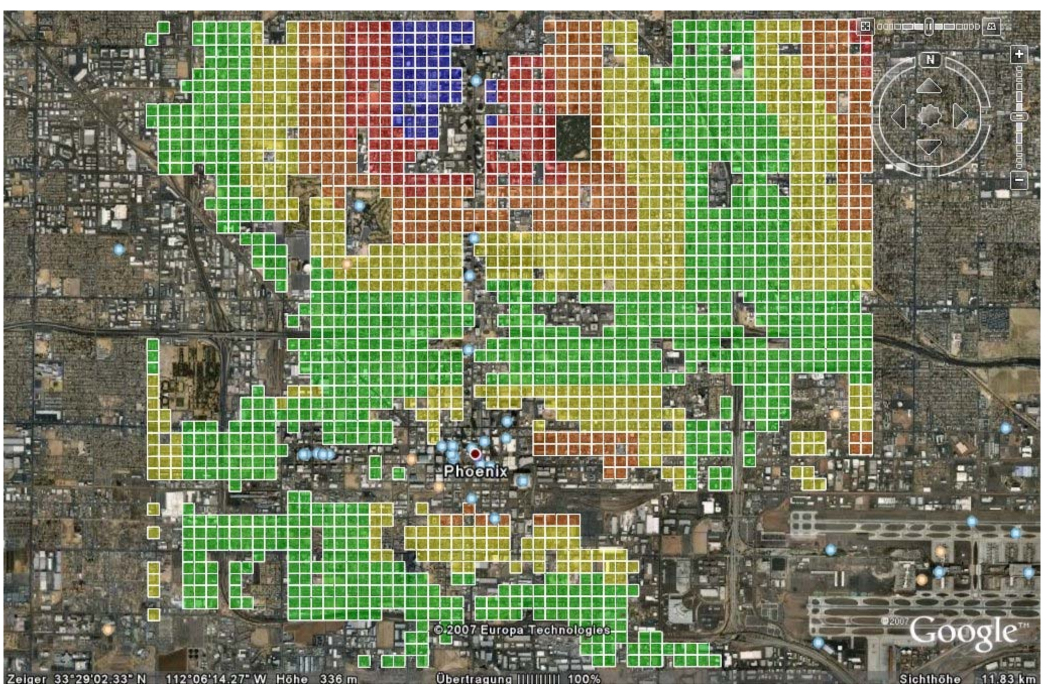

Figure 9: Phoenix Downtown, color-coded grid cells display distance to nearest highway

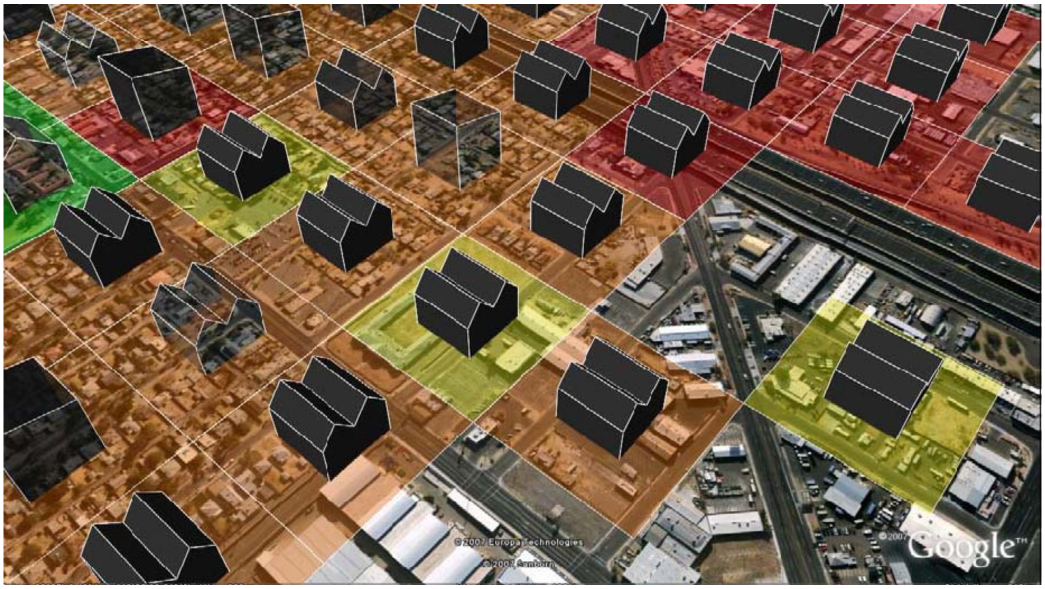

Figure 10: Close-up of icons for different building types

The examples above demonstrate that our approach is generic and dynamic and offers excellent accessibility of the information through a web-based, intuitive interface. Each Figure provides a means of visualizing multidimensional aspects of the data and offers an effective technique for examining relative patterns and relationships between different characteristics embedded in the information. Given that the procedure uses open geospatial data standards, it also offers an inexpensive yet powerful tool for spatial data visualization in three or more dimensions.

5. CONCLUSIONS

The motivation for this project was to develop an inexpensive, open-source visualization tool to communicate multidimensional attributes of a complex data set. The research also provided a means for visualizing future built environments and the characteristics of their inhabitants based on the textual output of the UrbanSim simulation package. UrbanSim, like most other urban futures projection models, offers very limited ability to visualize the output. Further, almost no land use change model offers effective means for visualizing information on built forms in three-dimensions. This paper bridges this gap in the current visualization literature dealing with urban forms. It also provides a path beyond the rule-based methods of procedural modelling towards a more empirically based framework for developing future environments.

Our visualization framework is not based on realism because realism is often unnecessary and inherently inaccurate for simulated future neighbourhoods even when the underlying data has a reasonable degree of certainty. The presented framework incorporates abstraction methods from cartography and Information Visualization to amplify cognition. Demographic and building type data is communicated to users as abstract geometries, scaled by attribute values, in 3D real context on Google Earth™. Our method provides realistic information without invoking high degree of photorealism that can distract attention from the complexity of information that needs to be communicated. It provides a 3-dimensional representation of abstract data to amplify cognition, and facilitate thinking, problem solving, and decision-making.

6. ACKNOWLEDGEMENTS

This work was supported by the German Science Foundation (DFG, grant number 1131) as part of the International Graduate School (IRTG) in Kaiserslautern on “Visualization of Large and Unstructured Data Sets. Applications in Geospatial Planning, Modelling, and Engineering”.

7. REFERENCES

[1] S. Guhathakurta, editor. *Integrated Urban and Environmental Models: A Survey of Current Applications and Research*, Springer, 2003.

[2] W. Förstner, "3D City Models: Automatic and Semiautomatic Acquisition Models", In *Photogrammetric Week '99*, pp. 291-303, Heidelberg, Wichmann Verlag, 1999.

[3] J. Hu, S. You, and U. Neumann, "Approaches to Large-Scale Urban Modelling", Computer Graphics and Applications, IEEE, Vol. 23(6):62-69, November 2003.

[4] C. Brenner, "Building Reconstruction from Images and Laser Scanning" International Journal of Applied Earth Observation and Geoinformation, Vol. 6(3-4):187-198, March 2005.

[5] H. Neidhart and M. Sester, "Creating a Digital Thermal Map Using Laser Scanning and GIS", In *Proceedings of the District Heat and Cooling Symposium*, Hannover, Germany, 2004.

[6] T. Lechner, B. A. Watson, U. Wilensky, and M. Felsen, "Procedural City Modeling", In *1st Midwestern Graphics Conference*, St. Louis, MO, 2003.

[7] P. Wonka, M. Wimmer, F. Sillion, and W. Ribarsky, "Instant Architecture", Transactions on Graphics, SIGGRAPH 2003, Vol. 22(3):669-677, July 2003.

[8] P. Müller, G. Zeng, P. Wonka, and L. V. Gool, "Image-based Procedural Modeling of Facades", Proceedings of ACM SIGGRAPH 2007 /ACM Transactions on Graphics, Vol. 26(3), 2007.

[9] P. Müller, P. Wonka, S. Haegler, A. Ulmer, and L. V. Gool, "Procedural Modelling of Buildings", Proceedings of ACM SIGGRAPH 2006/ ACM Transactions on Graphics, Vol. 25(3):614-623, 2006.

[10] Y. I. H. Parish and P. Müller, "Procedural Modeling of Cities", In *Proceedings of ACM SIGGRAPH 2001*, pp. 301-308, New York, NY, USA, 2001, ACM Press.

[11] L. G. da Silveira and S. R. Musse, "Real-time Generation of Populated Virtual Cities". In *VRST '06: Proceedings of the ACM Symposium on Virtual Reality Software and Technology*, pp. 155-164, New York, NY, USA, 2006. ACM Press.

[12] T. Slocum, C. Blok, B. Jiang, A. Koussoulakou, D. Montello, S. Fuhrmann, and N. Hedley. "Cognitive and Usability Issues in Geovisualization". In *Cartography and Geographic Information Science*, Vol. 28:61-75, 2001.

[13] R. E. Klosterman, "The What if?" In *Planning Support Systems: Integrating Geographic information Systems, Models, and Visualization Tools*, pp. 263-284, Redlands, CA: Environmental Systems Research Institute and New Brunswick, NJ: Rutgers Center for Urban Policy Research, 2001, ESRI Press.

[14] M. Kwartler and R. Bernard. CommunityViz: an Integrated Planning Support System. In R. K. Brail and R. E. Klosterman, editors, Planning Support Systems: Integrating Geographic information Systems, Models, and Visualization Tools, pages 285_308, Redlands, CA: Environmental Systems Research Institute and New Brunswick, NJ: Rutgers Center for Urban Policy Research, 2001. ESRI Press.

[15] P. Waddell, "UrbanSim: Modeling Urban Development for Land Use, Transportation and Environmental Planning", Journal of the American Planning Association, Vol. 68(3):297-314, 2002.

[16] H. Joshi, S. Guhathakurta, G. Konjevod, J. Crittenden, and K. Li, "Simulating Impact of Light Rail on Urban Growth in Phoenix: an Application of UrbanSim Modelling Environment", In *Proceedings of the 7th Annual International Conference on Digital Government Research, DG.O 2006*, pp. 135-141, 2006.

[17] H. Chernoff and M. H. Rizvi, "Effect on Classification Error or Random Permutations of Features in Representing Multivariate Data by Faces", Journal of American Statistical Association, Vol. 70:548-554, 1975.

[18] F. B. Viégas, M. Wattenberg, F. van Ham, J. Kriss, and M. McKeon, "Many Eyes: A Site for Visualization at Internet Scale", In *Proceedings of the IEEE Symposium on Information Visualization (InfoVIS 2007)*, Sacramento, CA, 2007.

[19] J. Bertin, Semiology of Graphics, University of Wisconsin Press, 1967.

[20] G. L. Andrienko and N. V. Andrienko, "Interactive Maps for Visual Data Exploration", International Journal Geographic Information Science, Vol. 13(4):355-374, June 1999.

[21] A. Skupin and S. I. Fabrikant, "Spatialization Methods: A Cartographic Research Agenda for Non-Geographic Information Visualization", Cartography and Geographic Information Science, Vol. 30(2):95-115, 2003.

[22] A. Skupin, "From Metaphor to Method: Cartographic Perspectives on Information Visualization", In *Proceedings of the IEEE Symposium on Information Visualization (InfoVIS 2000)*, pp. 91-97, Salt Lake City, UT, USA, October 9-10 2000, Los Alamitos: IEEE Computer Society.

[23] G. Fuchs and H. Schumann, “Visualizing Abstract Data on Maps”, IV'00, Vol. 00:139-144, 2004.

[24] A. M. MacEachren, “Visualization - Cartography for the 21st century”, In *Proceedings of the 7th Annual Conference of Polish Spatial Information Assocaition*, Warsaw, Poland, May 1998.

[25] D. Guo, M. Gahegan, A. M. MacEachren, and B. Zhou, “Multivariate Analysis and Geovisualization with an Integrated Geographic Knowledge Discovery Approach”, Cartography and Geographic Information Science, Vol. 32(2):113-132, April 2005.

[26] A. Skupin and R. Hagelman, “Attribute Space Visualization of Demographic Change”, In *11th ACM GIS Symposium (GIS'03)*, New Orleans, Louisiana, USA, November 7-8 2003, ACM Press.

[27] A. M. MacEachren, M. Gahegan, W. Pike, I. Brewer, G. Cai, E. Lengerich, and F. Hardisty, “Geovisualization for Knowledge Construction and Decision Support”, IEEE Computer Graphics and Applications, Vol. 24(1):13-17, Jan/Feb 2004.

[28] M.-J. Kraak, “Visualization Viewpoints: Beyond Geovisualization”, IEEE Computer Graphics and Applications, Vol. 26(4):6-9, Jul/Aug 2006.

[29] L. D. Pinnel, M. Dockrey, A. J. B. Brush, and A. Borning, “Design of Visualizations for Urban Modeling”, In *VisSym '00: Joint Eurographics - IEEE TCVC Symposium on Visualization*, Amsterdam, The Netherlands, May 2000.

[30] Y. Schwartzman and A. Borning, “The Indicator Browser: A Web-Based Interface for Visualizing UrbanSim Simulation Results”, In *HICSS '07: Proceedings of the 40th Annual Hawaii International Conference on System Sciences*, p. 92, Washington, DC, USA, January 2007, IEEE Computer Society.

[31] C. Tominski, P. Schulze-Wollgast, and H. Schumann, “3D Information Visualization for Time Dependent Data on Maps”, In *IV '05: Proceedings of the Ninth International Conference on Information Visualisation (IV'05)*, pp. 175-181, Washington, DC, USA, 2005, IEEE Computer Society.

[32] A. Borning and P. Waddell, “Integrated Land Use, Transportation, and Environmental Simulation: UrbanSim Project Highlights”, In *DG.O '04: Proceedings of the 2004 Annual National Conference on Digital Government Research*, 2004, pp 1-2.

[33] A. Borning, P. Waddell, and R. Forster, “UrbanSim: Using Simulation to Inform Public Deliberation and Decision-Making”, In *Digital Government: Advanced Research and Case Studies*, Springer-Verlag, 2006, in press

[34] S. Guhathakurta, J. Holston, Y. Kobayashi, T. Lant, and M. Patel, “Digital Phoenix Project”, available online at: <http://www.digitalphoenix-asu.net>, 2007. (Last Accessed: 11-21-2007).

[35] U.S. Census Bureau. “Census 2000”, available online at: <http://www.census.gov>, 2007. (Last Accessed: 11-06-2007).

[36] PostgreSQL Global Development Group, “PostgreSQL”, available online at: <http://www.postgresql.org>, 2007. (Last Accessed: 10-23-2007).

[37] Refractions Research, “PostGIS”, available online at: <http://postgis.refractions.net>, 2005. (Last Accessed: 10-23-2007).

[38] Open Geospatial Consortium Inc, “OGC Simple Feature Specification”, Available online at: <http://www.opengeospatial.org/standards>, 2007, (Last Accessed: 10-30-2007).

[39] Google Inc., Google Earth, available online at: <http://earth.google.com/>, 2007. (Last Accessed: 11-23-2007).