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Validation and Demonstration of the Prescott Spatial Growth Model in Metropolitan Atlanta, Georgia

Maurice G. Estes, Jr., William L. Crosson, Mohammad Z. Al-Hamdan, Dale A. Quattrochi, and Hoyt Johnson III

Abstract: This paper provides results on the performance of the Prescott Spatial Growth Model to project land use in the Atlanta metropolitan area. The Prescott Spatial Growth Model is a tool that can be applied at fine or coarse spatial scales and can accommodate a wide range of user inputs to develop any number of growth rules for projecting land use. “Blind” simulations and “guided” simulations for the Atlanta region were performed for the 1980–2000 period to evaluate the performance of the model in the quantity and spatial distribution of urban growth. Quantitative comparisons of both the blind and guided simulations with actual land use were used to assess the model’s performance. The error in the quantity of land-use classes projected and the spatial arrangement of the classes was assessed. The model provides exceptional flexibility and good overall performance in projecting land use in this study.

BACKGROUND

Rationale

The Prescott Spatial Growth Model (PSGM), originally designed for commercial use, has been used to develop growth scenarios from which to evaluate environmental impacts of urbanization. To facilitate further use of the PSGM in scientific research, a rigorous verification and validation of the model’s capabilities is needed. Given the model’s previous use in the Atlanta region to perform growth projections, this was the logical choice for a study area to perform model verification and validation. This allowed the use of historical and current data for the Atlanta regional area (see Figure 1), which was modeled in previous work by the authors (Estes et al. 2006, 2007). The purpose of this project was to develop growth scenarios for the time period of 1980–2000 using historical population, employment and land-use data. The intent of this endeavor was to validate the PSGM through comparison of scenarios generated with “blind” growth projections and those generated using actual growth for the time period. The drivers of growth are ever-changing for elected officials come and go, planning practices evolve, and current “hot-button” issues change. An exact agreement between projected and observed growth is not possible because of the complexity of decision drivers, previous development trends, and the inherent political and social variability.

GROWTH MODELS

Numerous land-use and land-cover change (LULCC) models have been developed with various perspectives. Growth models may be spatial or nonspatial and typically are used for prediction and scenario generation in the context of integrated assessments of LULCC. Such models usually are implemented at local scales and may not be scalable to continental or global scales. Growth models may be grouped into two broad categories, empirical models and dynamic process simulation models. Empirically fitted models are based on statistically matching temporal trends and/or spatial patterns with a set of predictor variables (Brown et al. 2004).

Dynamic process models seek to represent the most important interactions between agents, organisms, and their environment (Brown et al. 2004). Examples of process models are cellular automata (CA) (Clarke and Gaydos 1998) and agent-based models (ABMs) White and Engelen 1993). In CA models, cells have fixed neighborhood relations and update rules. In some cases, the CA represents the state and dynamics of the environment. Cells can represent parcels of land with unique characteristics, each changing as a result of rules applied to the state of the cell and that of its neighbors. Challenges include how to establish rules that govern system behavior and incorporating heterogeneity and dynamism in these rules (Brown et al. 2004).

A widely used CA model is SLEUTH (Clarke et al. 1997) in

Figure 1. Map of Georgia and surrounding states showing the 13-county study area
which each grid cell is classified as either urbanized or nonurbanized. Such CA models are probabilistic, run quickly, and can be applied to any region with the necessary data. However, they lack the ability to distinguish activity types for they operate on simple “urban” and “nonurban” designations. The SLEUTH model runs in the UNIX environment and requires a tremendous amount of spatial data. The model also has neither coherent economic theory nor a behavioral component to help understand its results (EPA 1999).

Agent-based models (ABMs) are defined in terms of entities and dynamics at microlevels such as individuals (householders, farmers, developers) and/or institutions (industries, governments, etc.). Agents need their state to be defined, decision-making rules developed, and other mechanisms to perform particular behaviors. Agents’ behaviors affect each other and the environment. The environment changes in response to agents and by following its own dynamics. This allows complex feedback relationships that lead to nonlinear path-dependent dynamics often observed in complex systems. ABMs are considered a promising topic for continued development (Brown et al. 2004). These models require detailed knowledge of the behavior of the agents being modeled. They also may require considerable coding expertise as well as considerable computer time to run. In addition, they typically require many simulations to evaluate any particular situation for they are based on an underlying stochastic model.

The PSGM, developed at Prescott College in Prescott, Arizona, in collaboration with NASA, is a dynamic process model with a raster-based structure that is compatible with agent-based features. This GIS-based model allows users to build a variety of future community growth scenarios based on current policy and development decisions. It is important to note that the PSGM is projective not predictive. The validation process allowed us to see how well our rules captured past growth activity. Validating that the PSGM does this reliably allows a reasonable confidence that the rules used to replicate past growth can also project future growth under the same scenario assumptions. Scenarios may be created at the parcel level or by the use of any size-assigned grid cells. The PSGM may be constructed as a set of “nested” models moving from the county to the community and potentially the neighborhood level. As the PSGM is a grid-based model, the suitability or land-use allocation results can be transferred to parcels through an overlay process afterwards. Also, one of the strengths of the PSGM is that, once the input data are set up for a baseline, adjustments can be made to reflect the impact of faster or slower growth, different distributions of growth, and other factors that may impact the growth rate and dispersion of the population. This type of approach allows the user to realistically represent each area’s particular rate and distribution of growth. The PSGM is not as data-intensive as other GIS-based spatial growth models such as the INDEX (EPA 1999) and the California Urban Futures (CUF) model (Landis 1995), which require detailed data for raw land prices, construction costs, site improvement costs, service costs, development fees, and other development costs.

THE PRESCOTT SPATIAL GROWTH MODEL AND METHODOLOGY

Model Description

The PSGM is an ArcView GIS compatible application that allocates future growth into available land based on user-defined parameters. The purpose of the PSGM is to help users develop alternative future patterns of land use based on socioeconomic projections such as population, employment, and other controlling factors. When creating scenarios based on future development, the PSGM requires several inputs. Developable land must be provided as an input grid that represents areas suitable for accepting future growth. Growth projections quantify the demand for land area to be developed for each time horizon for each land-use type. These projections are derived from socioeconomic drivers in a PSGM utility that determines the growth for each land-use category (industrial, high-density residential, etc.). Suitability rules for the location of future growth are specified using a PSGM table interface. When the PSGM runs, it allocates the new growth onto the developable land grid in the order of most to least suitable land and in user-defined order for land-use type (e.g., user decides that for each time step land use x gets first choice of available land, then y, then z). The output of the PSGM is a series of growth grids, one for each time step and land-use type, showing the anticipated future growth pattern.

The creation of a set of growth rules provides the basis for allocating new types of development and to specify land restricted from development. Each rule is assigned a priority weight in relation to the other rules to reflect the assumptions of the scenario being developed. The model output will reflect the complex aggregation of these rules. A separate rule set is created for each land-use class being assessed in the model. The various rule sets then are run consecutively in a comprehensive model simulation, letting each rule set allocate land based on available area and priority. In each scenario, once land is used up by one type of development, it becomes unavailable to any other land-use type. The model also notifies the user if there is insufficient land to meet the demand of a particular rule set. There is no limit on the number of rules in a rule set or the number of rule sets in a scenario. Model run time varies widely depending on the number of rules used, the size of the land bank, and the scale of the grid, lot, or parcel resolution to be utilized provided the data are in raster format.

OVERVIEW OF COMPOSITE SUITABILITY LOGIC

Each suitability rule created by the user belongs to a specific land-use type. Each land-use type can have 1 to N suitability rules. Each rule is used to create an individual suitability grid and if there
is more than one rule, the individual suitability grids are added to create a composite suitability grid for that land-use category. This is the grid that is used to allocate growth assigned to that land-use type. The process is outlined as follows:

Determine the rule type and the associated parameters for each land use and user-selected growth scenario (i.e., distance, distance units, threshold, density, etc.).

Apply the rule and normalize (slice) the resulting suitability values on a 1 to 10 scale using the equal interval option. For example, if a “distance from” rule is run using major roads as a reference theme and the distance is one mile, the threshold is “LT 1” and “More Is Better = False,” then a one-mile buffer is generated around roads and the suitability within the buffer area is set as 10 for cells closest to the road and 1 for those further away.

Multiply the suitability grid by its weight.

Add each suitability grid for the current model together.

OVERVIEW OF GROWTH ALLOCATION

Each land-use type that is selected by the user results in a composite suitability grid with higher values representing the more suitable areas. The growth allocation portion of the PSGM assigns growth (in the form of acres) for each land-use category and a time step to the composite suitability grid (CSG). As land is allocated, it is removed from consideration by the model in the allocation of other land-use needs. If there is not enough suitable land to accommodate the growth, the user is warned and that model is not allocated for future time steps.

The sequence of allocation is in land-use type order (user-defined) by time step. So each land-use type is run for the current time step and then the next time step is run. For example, if there were a set of four rules for Single Family Growth in ten-year intervals to 2050, the model would generate four grids representing each rule, one CSG, and grids that represent Single Family Growth in 2010, 2020, 2030, 2040, and 2050. These sets of grids are created for each rule set run for a given scenario. These grids then can be merged by land-use type, year of growth, etc., to display different scenario data for assessment. Figure 2 shows how separate rules are combined to create a CSG, in this case for commercial development. Each of the three rule grids shown has an assigned weight and encompasses all counties within the region. Within each county there also is a rule that attracts growth within the county. This rule, when combined with the others, results in the CSG shown for one county—Gwinnett—in the eastern part of the figure.

SCENARIOS

The projection period for this study is from the years 1980 to 2000. Both blind and guided model simulations were performed to evaluate land-cover land-use (LCLU) changes in the years 1990 and 2000. Blind simulations use existing trend data for model inputs that existed prior to 1980 and guided simulations use Census data for the projection period. Observed data in the form of classified LCLU from Landsat were used to evaluate model accuracy or performance.

Figure 2. Top: three of the rules used for commercial development in Gwinnett County, Georgia; bottom: composite suitability grid for commercial development in Gwinnett County
Validation Procedure

Within the context of growth modeling, performing or even defining validation is a difficult task. Projections of a future state cannot be validated, but the performance of the model can be evaluated in “hind-cast” mode, in which projections are made from some past starting point and results are compared with observed LCLU at the simulation end time (Liu et al. 2007). White (2006) proposed two pattern-based techniques—a fuzzy polygon-based matching method and fractal analysis—to compare maps. Pontius and Schneider (2001) described using the “relative operating characteristic” as a quantitative measurement of performance of a land-cover change model.

In this research, we have taken a somewhat different approach in which we assume that in validating growth model results, it is important to isolate the effects of four sources of uncertainty in the modeling system: (1) errors in model inputs (population and employment projections, road network); (2) errors in model parameters (e.g., dwelling units per acre, persons per household); (3) errors in model formulation (growth rules); and (4) random errors. If model inputs and parameters were known exactly, the first two error sources would vanish and the growth model would develop exactly the correct amount of land for residential and commercial use in each county. However, the distribution of development still would be imperfectly modeled because of the latter two error sources, which control the spatial patterns but not the amount of growth. Growth rules control the proximity of growth to existing development and to the road network and the “clustering” of development. “Random errors” contribute to an inaccurate spatial distribution of development.

A projection made from a past starting point using only data available at that time, i.e., a “blind” simulation, will be affected by all four types of errors. Comparison of a blind simulation made for the year 2000 from a 1980 starting point to observed land-use patterns in 2000 allows a quantification of the effects of these errors. It is possible to minimize errors of the first type by providing as model inputs the actual population and employment data available from U.S. Census reports or other sources throughout the model simulation period. If we also utilize population and housing data for the projection period to calibrate model parameters, type 2 errors can be reduced (but not eliminated), leaving types 3 and 4 errors as the primary sources of uncertainty. This “guided” simulation provides better estimates of parameters such as jobs per acre than in the blind projection. By comparing the guided forecast with the observed growth for the 1980–2000 simulation period, the effects of errors in growth rules can be estimated. Given that the development of growth rules is a mixture of art and science, a trial-and-error process was followed to evaluate the impacts of errors that resulted from rule modifications.

Data Inputs for Blind and Guided Simulations

Population

County-level data obtained from the Atlanta Regional Commission (ARC) and from the U.S. Census report were used to create two population tables, one for the blind simulation and one for the guided simulation. For the blind simulation, the population trends for each county, obtained from the 1970 and 1980 Census data, were used to extrapolate county populations through 2000. As shown in Figure 3, there are significant differences between the actual 2000 populations used in the guided simulation and those extrapolated from the 1970–1980 trends for the blind simulation. Overall, the population forecast used in the blind simulation overestimates population in 2000 by about 15 percent (see Figure 4).

Figure 3. Census population data for the 13 metropolitan Atlanta counties in 1980 and 2000 and the projected 2000 population used in the blind simulation

Figure 4. Thirteen-county metropolitan Atlanta total census population data used in guided simulation and extrapolated population used in blind simulations at five-year intervals, 1980–2000
4), but overestimates or underestimates greatly in certain counties.

To determine the required high-density residential (HDR) and low-density residential (LDR) populations by county for the blind run, we used 1980 Census data describing the percentage “urban” and percentage “rural” populations, as well as the urban and rural population changes from 1970 to 1980. Assuming that the trends in urban population approximate the trends in HDR population, we projected the urban population trend in five-year intervals to 2000 to define the percentage HDR and the total HDR and LDR populations for each county. These were used in the blind model simulations.

For the guided run, actual county populations were used for Census years (1980, 1990, 2000), with interpolation used for the intervening years. Additionally, we realized that using the Census urban/rural population splits to directly define the HDR and LDR populations without considering urbanized area definitions would be inaccurate. In the Census reports, urban population was split into three parts: in places of 50,000 people or more (U1), in places of 10,000–50,000 (U2), and in places of 2,500–9,999 (U3). Because not all of this “urban” population resides in HDR areas, we assumed that the percentages of the population in these three types of communities that live in HDR areas are 70 percent, 20 percent, and 10 percent, respectively. This leads to the formula:

\[
\text{HDR population} = 0.7 \times (U1) + 0.2 \times (U2) + 0.1 \times (U3).
\]

The HDR populations were interpolated for 1985 and extrapolated for 1995 and 2000. LDR populations then were calculated as the difference between total and HDR populations. Figure 5 shows the percentage of HDR populations for the blind and guided simulations at five-year intervals from 1980 to 2000. The guided percentage of HDR values remained nearly constant over this period, while the blind forecast values, derived as discussed previously, increased from 57 percent to 71 percent.

**EMPLOYMENT**

Employment data from the U.S. Census exist in the form of number of jobs per county, including total, net change, and percentage change. Using the 1980 land-use base map (described in the next section), the number of acres for each land-use type was determined for each county, from which the number of jobs/acre was calculated for the blind simulation (see Table 1). Holding this ratio constant and continuing the 1970–1980 job growth rate, the number of jobs per county was determined for the 1980–2000 time period. For the blind simulation, we did not include commercial land use for three counties (Coweta, Forsyth, and Paulding) for which we did not have employment data for this time frame.

For the guided simulation, an adjustment was made to better define the jobs/acre ratio for the projection time period. We used the LandPro99 Commercial, Commercial/Industrial, and Industrial land-use classes and calculated the jobs/acre ratio as the number of jobs in 1999 (from ARC) to the number of acres classified as one of these three LandPro99 classes. As a result of this modification, jobs/acre ratios for the guided simulation were much higher than for the blind simulation (see Table 1).

![Figure 5](image-url) **Figure 5.** High-density residential (HDR) population as a percentage of the total population for the guided (Census values) and blind forecasts at five-year intervals, 1980–2000

![Figure 6](image-url) **Figure 6.** Number of jobs in ten of the 13 metropolitan Atlanta counties in 1980 and 2000 and the projected 2000 jobs used in the blind simulation. Data not available for the other three counties
Table 1. Jobs per acre used in the blind and guided simulations

<table>
<thead>
<tr>
<th>County</th>
<th>Blind</th>
<th>Guided</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cherokee</td>
<td>7.1</td>
<td>7.7</td>
</tr>
<tr>
<td>Clayton</td>
<td>4.0</td>
<td>12.5</td>
</tr>
<tr>
<td>Cobb</td>
<td>6.7</td>
<td>14.3</td>
</tr>
<tr>
<td>DeKalb</td>
<td>12.5</td>
<td>16.7</td>
</tr>
<tr>
<td>Douglas</td>
<td>2.2</td>
<td>7.1</td>
</tr>
<tr>
<td>Fayette</td>
<td>1.9</td>
<td>7.7</td>
</tr>
<tr>
<td>Fulton</td>
<td>16.7</td>
<td>20.0</td>
</tr>
<tr>
<td>Gwinnett</td>
<td>5.3</td>
<td>11.1</td>
</tr>
<tr>
<td>Henry</td>
<td>2.0</td>
<td>5.9</td>
</tr>
<tr>
<td>Rockdale</td>
<td>3.4</td>
<td>9.1</td>
</tr>
</tbody>
</table>

The number of jobs for each county at each time step was obtained from Census data; these data were used directly in the guided simulation. For the blind simulation, the number of jobs in each county was determined from the jobs/acre ratio and the projection of the 1970–1980 job growth rate, as discussed previously. Figure 6 shows the number of jobs by county in 1980 and the blind and guided projections for 2000. The blind projections of jobs overestimate the actual number of jobs in some counties and underestimate in others. The blind simulation overestimates the total number of jobs in these ten counties by about 28 percent.

**OBSERVED LAND-USE DATA**

Classified Landsat data from the Thematic Mapper™ in 1990 and the Enhanced Thematic Mapper Plus (ETM+) sensor in 2000 at 30-meter spatial resolution were used as ground truth baselines from which model simulations were compared to evaluate accuracy. Image processing included rectification with Digital Line Graph data and atmospheric correction using a modified form of the dark object subtraction technique (Chavez 1988). Supervised training and classification of segments were performed to produce a 16-class land-cover land-use data set (Laymon 2004). Each land-use classification provides commercial, HDR, and LDR developed land-use types as well as undeveloped classes.

To use these data effectively, there must be a relationship between these land uses and information available in the population data as discussed previously. Land-use data standardization is an important consideration and the 1980, 1990, and 2000 data do cover the same geographic area and contain the same land-use types. Differences in image resolution and spectral range contribute to some errors in classification and lead to model simulation errors. For example, the coarser resolution of 1980 data likely results in some low-density residential development being classified as forest or agricultural classes.

**TRANSPORTATION DATA**

A road network is a required model input for the PSGM. The level of detail can vary depending on data availability and output requirements. For model validation of the blind simulation, we used the primary road network, including only interstate, U.S., and major state highways that existed in 2000 (see Figure 7, left). These data were obtained from SMARTRAQ, which was developed in 1997 by the Georgia Tech Research Institute as a
detailed database of land use for the 13-county metropolitan Atlanta region, which contains several classes of roads. This input is reasonable for the blind simulation given that the major road network experienced few changes between 1980 and 2000. Conversely, the secondary road network experienced significant modifications. For the guided simulation, we used a road network of primary and secondary roads from available USGS data at the Georgia Data Clearinghouse (see Figure 7, right).

**MODEL ASSUMPTIONS AND PARAMETERS**

### Rules Development

The development of rule sets is critical to the successful function of the PSGM. In the Atlanta study area, each county had its own set of population predictions as described previously. Additionally, the distribution of population by residential land-use type (HDR, LDR) was calculated for each county. A standard set of rules was developed and used for all counties. For this study, the 1980 land-use base contains only one land-use type (urban) that can be used to attract and allocate commercial growth; so for each county, the net change in number of jobs was applied solely to this land-use type.

In running the model, we projected growth of commercial, HDR, and LDR land-use types separately. The trend in the Atlanta area seems to revolve around some basic rules governing where growth occurs, typically along transportation corridors, near existing commercial development, near existing development of the same type, forming the basis for the rule sets, which are shown in Table 2.

The Atlanta region has few barriers to expanding growth; there are no significant mountains or other geographic obstructions. This results in a large amount of land being equally attractive for new development. An additional rule was included directing each county’s growth to remain in that county. However, should a county fill up with a given land-use type, development will overflow into adjacent counties, using the other rules set up for that land use.

In the blind simulation, dwelling units per acre (DUAC) and persons per household unit (PPHU) values were assigned using only general urban planning guidelines (Kindel 2006) and local knowledge. The assigned DUAC values for LDR ranged from 1 for rural counties to 2 for urban counties, while HDR DUACs ranged from 4 for rural counties to 7 for urban counties (see Table 3).

In the guided simulation, we first calculated DUAC values for each county based on the county populations and other Census data using the following procedure. First, PPHU for LDR and HDR were set to 2.54 and 2.41, respectively, based on 1990

### Table 2. Rule sets for the blind and guided simulations. Rules 1 to 4 each use a distance and weight as shown for each land-use type. Rule 2 was not used for low-density residential in the guided simulation.

<table>
<thead>
<tr>
<th>Rule Type</th>
<th>Commercial</th>
<th>High-density Residential</th>
<th>Low-density Residential</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Distance (Miles)</td>
<td>Weight</td>
<td>Distance (Miles)</td>
</tr>
<tr>
<td>1. In county—develop land in respective county first</td>
<td>1.0</td>
<td>10</td>
<td>1.0</td>
</tr>
<tr>
<td>2. Near roads—within x miles of major roads</td>
<td>0.5</td>
<td>4</td>
<td>2.0</td>
</tr>
<tr>
<td>3. Within x miles of existing development of same type</td>
<td>0.75</td>
<td>4</td>
<td>2.0</td>
</tr>
<tr>
<td>4. Follow new growth—within x miles of new development of same type</td>
<td>0.75</td>
<td>2</td>
<td>2.0</td>
</tr>
<tr>
<td>5. Random—allows spontaneous development</td>
<td>Not Used</td>
<td>Used</td>
<td>6</td>
</tr>
</tbody>
</table>

### Table 3. Dwelling units per acre (DUAC) assigned for each county for low-density residential (LDR-guided and HDR-blind) and high-density residential (HDR-guided and HDR-blind) land-use types

<table>
<thead>
<tr>
<th>County</th>
<th>LDR Guided and Blind</th>
<th>HDR Guided</th>
<th>HDR Blind</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cherokee</td>
<td>1.0</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Clayton</td>
<td>1.5</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Cobb</td>
<td>2.0</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Coweta</td>
<td>1.25</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>DeKalb</td>
<td>1.25</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>Douglas</td>
<td>1.25</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>Fayette</td>
<td>1.25</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Forsyth</td>
<td>1.25</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Henry</td>
<td>1.25</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>Paulding</td>
<td>1.25</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Rockdale</td>
<td>1.25</td>
<td>4</td>
<td>5</td>
</tr>
</tbody>
</table>
Figure 8. Distribution of commercial land use in 1980 and 2000 (upper panels) and projected for 2000 by the blind and guided simulations (bottom panels); percent coverage for each county labeled.
Figure 9. Distribution of high-density residential land use in 1980 and 2000 (upper panels) and projected for 2000 by the blind and guided runs (bottom panels); percent coverage for each county labeled.
Figure 10. Distribution of observed LDR land use in 1980 and 2000 (upper panels) and projected for 2000 by the blind and guided simulations (bottom panels); percent coverage for each county labeled.
Census data. Next, LDR and HDR acres for each county were obtained from the 2000 land-use map. The numbers of LDR and HDR units then were calculated from the LDR/HDR populations and PPHU values. Finally, the DUAC values for HDR and LDR classes were determined from the numbers of LDR and HDR units and the LDR and HDR acreages. However, because of classification errors and other uncertainties, DUAC values at the county level varied outside of a range deemed acceptable. Therefore, using the 13-county average DUAC values as guidance, we assigned DUACs in a manner that captured the urban, suburban, or rural nature of each county. Assigned LDR DUACs for the guided simulation were the same as for the blind simulation, ranging from 1 to 2, and HDR DUACs for the guided simulation were slightly lower than for the blind simulation, ranging from 3 to 6 (see Table 3).

**RESULTS**

Using the inputs and rule sets described in the previous sections, the blind and guided simulations were performed starting from the same 1980 Landsat observed data to predict land use in the year 2000. Figures 8 to 11 display the 1980 and 2000 observed data resampled to 90 meters for the three developed categories under analysis: commercial, HDR, and LDR. Also shown in these figures are the blind and guided simulations of each land-use category for the year 2000 at a 90-meter spatial resolution. Comparison of the blind and guided simulations for 2000 to the observed data indicates that the model is capturing development trends. This is most notable in the HDR and commercial land-use categories that tend to follow major transportation arteries. The guided simulation better represents the LDR spatial pattern than does the blind simulation, although both simulations underestimate LDR development. However, this error seems to be related in part to an apparent underestimation of LDR land use in the 1980 observed data (see the discussion at the end of this section).

As shown in Figure 8, the model captures the spatial commercial development trends in both the blind and guided simulations. The amount of commercial growth is overestimated in the blind simulation, particularly in areas more distant from the central business district. The total commercial land use in the guided simulation compares very favorably with the 2000 observed data.

Figure 9 shows that the model accurately captures spatial trends and the amount of HDR development in both simulations, with the guided simulation very highly correlated with the 2000 observed data. The blind simulation slightly overestimates HDR growth.

The model captures overall spatial trends for LDR development particularly in the guided simulation (see Figure 10), although both simulations underestimate the amount of LDR in 2000. The blind run clusters development too much along roadways in Cherokee County, along the Fulton-Forsyth boundary, and in Rockdale County. Overall, more dispersion and less clustering would improve the spatial output from the guided

### Table 4. Kappa statistics for the 1990 and 2000 projected land-use model outputs

<table>
<thead>
<tr>
<th>Class</th>
<th>Observed Agreement</th>
<th>Chance Agreement</th>
<th>Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990 Guided Projected Land Use</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban Commercial</td>
<td>0.96</td>
<td>0.93</td>
<td>0.42</td>
</tr>
<tr>
<td>High-density Residential</td>
<td>0.89</td>
<td>0.85</td>
<td>0.28</td>
</tr>
<tr>
<td>Low-density Residential</td>
<td>0.91</td>
<td>0.91</td>
<td>0.004</td>
</tr>
<tr>
<td>Entire Urban</td>
<td>0.84</td>
<td>0.72</td>
<td>0.41</td>
</tr>
<tr>
<td>1990 Blind Projected Land Use</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban Commercial</td>
<td>0.95</td>
<td>0.92</td>
<td>0.40</td>
</tr>
<tr>
<td>High-density Residential</td>
<td>0.89</td>
<td>0.85</td>
<td>0.28</td>
</tr>
<tr>
<td>Low-density Residential</td>
<td>0.92</td>
<td>0.92</td>
<td>0.003</td>
</tr>
<tr>
<td>Entire Urban</td>
<td>0.83</td>
<td>0.72</td>
<td>0.40</td>
</tr>
<tr>
<td>2000 Guided Projected Land Use</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban Commercial</td>
<td>0.95</td>
<td>0.92</td>
<td>0.35</td>
</tr>
<tr>
<td>High-density Residential</td>
<td>0.87</td>
<td>0.83</td>
<td>0.26</td>
</tr>
<tr>
<td>Low-density Residential</td>
<td>0.83</td>
<td>0.81</td>
<td>0.006</td>
</tr>
<tr>
<td>Entire Urban</td>
<td>0.78</td>
<td>0.64</td>
<td>0.40</td>
</tr>
<tr>
<td>2000 Blind Projected Land Use</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban Commercial</td>
<td>0.94</td>
<td>0.91</td>
<td>0.32</td>
</tr>
<tr>
<td>High-density Residential</td>
<td>0.87</td>
<td>0.82</td>
<td>0.27</td>
</tr>
<tr>
<td>Low-density Residential</td>
<td>0.83</td>
<td>0.82</td>
<td>0.006</td>
</tr>
<tr>
<td>Entire Urban</td>
<td>0.78</td>
<td>0.62</td>
<td>0.43</td>
</tr>
</tbody>
</table>

### Table 5. Moran’s I for the year 2000 observed land use and projected land use for 2000 model simulations

<table>
<thead>
<tr>
<th>Class</th>
<th>Observed</th>
<th>Guided Projected</th>
<th>Blind Projected</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban Commercial</td>
<td>0.89</td>
<td>0.94</td>
<td>0.93</td>
</tr>
<tr>
<td>High-density Residential</td>
<td>0.90</td>
<td>0.90</td>
<td>0.89</td>
</tr>
<tr>
<td>Low-density Residential</td>
<td>0.91</td>
<td>0.79</td>
<td>0.82</td>
</tr>
</tbody>
</table>
Figure 11. Distribution of the three developed land uses in 1980 and 2000 (upper panels) and projected by the blind and guided simulations (bottom panels)
simulation. Figure 11 (a composite of Figures 8 through 10) shows the 1980 and 2000 maps of all land-use classes along with the blind and guided simulation results.

Kappa statistics and Moran’s I were computed to evaluate the spatial accuracy of the model’s projected 1990 and 2000 land use. The Kappa statistic is an index that compares the agreement against that which might be expected by chance. Kappa can be thought of as the chance-corrected proportional agreement, and possible values range from +1 (perfect agreement) to 0 (no agreement above that expected by chance) to -1 (complete disagreement). Kappa statistics for each developed land-use class are shown in Table 4.

The Kappa statistics in Table 4 are computed for each developed class predicted by the model and “entire urban” or an aggregate of all developed classes. Overall, the observed agreement is higher than the chance agreement, though the possibility of chance agreement is high for all classes. The Kappa statistic is higher for most developed classes in the guided simulation compared to the blind simulation; however, the differences are very small. The model’s performance in predicting LDR was the lowest among the developed classes as indicated by the very low Kappa statistic for this class.

Given a set of features and an associated attribute, global Moran’s I evaluates whether the pattern expressed is clustered, dispersed, or random. A Moran’s I value near +1.0 indicates

Table 6. Projected land use, in number of pixels and in percentage of study area, for blind and guided simulations compared to year 2000 base map

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pixels</td>
<td>%</td>
<td>Pixels</td>
</tr>
<tr>
<td>Undeveloped</td>
<td>724,662</td>
<td>59.1</td>
<td>827,617</td>
</tr>
<tr>
<td>Commercial</td>
<td>67,159</td>
<td>5.2</td>
<td>117,211</td>
</tr>
<tr>
<td>High-density Residential</td>
<td>178,860</td>
<td>13.9</td>
<td>215,295</td>
</tr>
<tr>
<td>Low-density Residential</td>
<td>280,871</td>
<td>21.8</td>
<td>107,189</td>
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</table>

Table 7. Definition of possible model errors

<table>
<thead>
<tr>
<th>Error Category</th>
<th>2000 Observed</th>
<th>Model Projection</th>
</tr>
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<tbody>
<tr>
<td>-6</td>
<td>Urban</td>
<td>Undeveloped</td>
</tr>
<tr>
<td>-5</td>
<td>HDR</td>
<td>Undeveloped</td>
</tr>
<tr>
<td>-4</td>
<td>LDR</td>
<td>Undeveloped</td>
</tr>
<tr>
<td>-3</td>
<td>Urban</td>
<td>LDR</td>
</tr>
<tr>
<td>-2</td>
<td>HDR</td>
<td>LDR</td>
</tr>
<tr>
<td>-1</td>
<td>Urban</td>
<td>HDR</td>
</tr>
<tr>
<td>0</td>
<td>Urban, HDR, LDR, or Undeveloped</td>
<td>Correct Projection</td>
</tr>
<tr>
<td>1</td>
<td>HDR</td>
<td>Urban</td>
</tr>
<tr>
<td>2</td>
<td>LDR</td>
<td>HDR</td>
</tr>
<tr>
<td>3</td>
<td>LDR</td>
<td>Urban</td>
</tr>
<tr>
<td>4</td>
<td>Undeveloped</td>
<td>LDR</td>
</tr>
<tr>
<td>5</td>
<td>Undeveloped</td>
<td>HDR</td>
</tr>
<tr>
<td>6</td>
<td>Undeveloped</td>
<td>Urban</td>
</tr>
</tbody>
</table>
Table 8. Model performance in urban zone 1 by type of error

<table>
<thead>
<tr>
<th>VALUE</th>
<th>COUNT</th>
<th>VALUE</th>
<th>COUNT</th>
</tr>
</thead>
<tbody>
<tr>
<td>-6</td>
<td>313</td>
<td>-6</td>
<td>401</td>
</tr>
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<td>-5</td>
<td>2888</td>
<td>-5</td>
<td>2692</td>
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<td>-4</td>
<td>960</td>
<td>-4</td>
<td>1074</td>
</tr>
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<td>-3</td>
<td>8</td>
<td>-3</td>
<td>8</td>
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<td>1397</td>
<td>2</td>
<td>1345</td>
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<td>381</td>
<td>3</td>
<td>319</td>
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<td>95</td>
<td>4</td>
<td>93</td>
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<td>510</td>
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<td>460</td>
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<tr>
<td>Total</td>
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</table>

Table 9. Model performance in suburban zone 2 by type of error

<table>
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<th>COUNT</th>
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<tbody>
<tr>
<td>-6</td>
<td>935</td>
<td>-6</td>
<td>801</td>
</tr>
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<td>-5</td>
<td>2667</td>
<td>-5</td>
<td>2532</td>
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<td>-4</td>
<td>8230</td>
<td>-4</td>
<td>7762</td>
</tr>
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<td>-3</td>
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<td>-3</td>
<td>46</td>
</tr>
<tr>
<td>-2</td>
<td>177</td>
<td>-2</td>
<td>153</td>
</tr>
<tr>
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<td>1054</td>
<td>-1</td>
<td>1186</td>
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<td>0</td>
<td>9941</td>
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<td>1388</td>
<td>1</td>
<td>1369</td>
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<td>187</td>
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<td>636</td>
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<td>Total</td>
<td>32372</td>
<td>Total</td>
<td>32372</td>
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</table>

Table 10. Model performance in rural zone 3 by type of error

<table>
<thead>
<tr>
<th>VALUE</th>
<th>COUNT</th>
<th>VALUE</th>
<th>COUNT</th>
</tr>
</thead>
<tbody>
<tr>
<td>-6</td>
<td>652</td>
<td>-6</td>
<td>693</td>
</tr>
<tr>
<td>-5</td>
<td>2765</td>
<td>-5</td>
<td>2947</td>
</tr>
<tr>
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<td>-4</td>
<td>4680</td>
</tr>
<tr>
<td>-3</td>
<td>89</td>
<td>-3</td>
<td>54</td>
</tr>
<tr>
<td>-2</td>
<td>332</td>
<td>-2</td>
<td>188</td>
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<td>59</td>
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<td>737</td>
</tr>
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<td>Total</td>
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<td>Total</td>
<td>24737</td>
</tr>
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</table>

Table 11. Model performance in the total model domain by type of error

<table>
<thead>
<tr>
<th>VALUE</th>
<th>COUNT</th>
<th>VALUE</th>
<th>COUNT</th>
</tr>
</thead>
<tbody>
<tr>
<td>-6</td>
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<td>14949</td>
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<tr>
<td>-5</td>
<td>81201</td>
<td>-5</td>
<td>71443</td>
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<td>-4</td>
<td>178211</td>
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<td>3219</td>
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<td>29937</td>
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<td>59447</td>
<td>2</td>
<td>65501</td>
</tr>
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<td>16629</td>
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<td>30294</td>
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<tr>
<td>Total</td>
<td>1285336</td>
<td>Total</td>
<td>1285339</td>
</tr>
</tbody>
</table>
clustering, while a value near –1.0 indicates dispersion. Table 5 provides Moran’s I values for each developed class.

The Moran’s I results indicate the degree that model outputs are spatially clustered or dispersed for comparison to the year 2000 observed land-use targets. Both guided and blind projections have comparable autocorrelation values to the year 2000 observed land-use targets. Spatial patterns for the urban commercial and HDR classes are more like the year 2000 observed land use than the LDR class.

Table 6 quantifies model performance in terms of land-use percentages, total pixel changes, and land-use change from 1980 to 2000. Comparisons are made of each land-use category in 2000 to blind and guided land-use projections as well as the percent differences relative to the 2000 base map. Overall, the percent of total pixels being correctly projected by the model is good. Commercial land use is significantly overprojected, LDR is significantly underprojected, and HDR slightly overprojected in the blind simulation. For the guided simulation, the same biases exist but to a much lesser extent.

SUBREGIONAL ANALYSIS

In addition to the analysis of overall model performance, subregions of the modeling domain were selected for an in-depth evaluation of model performance. Three subregions of comparable size were selected as noted in Figure 12. The subregions depict three representative growth environments commonly found in the modeling domain. Urban zone 1 depicts an area of the central business district and surrounding midtown residential and commercial development. High-density residential development is more common than low-density residential development in this zone. Suburban zone 2 is an area of rapidly expanding commercial and residential growth along the Interstate 75 corridor. This zone is a dynamic mixture of expanding commercial and both HDR and LDR development. Rural zone 3 is an area of undeveloped land and LDR development in 1980 that has been impacted by urban sprawl and primarily an increase in LDR development over the simulation period.

Model performance in the subregions was evaluated based on a set of potential model errors as noted in Table 7. For example, error 1 denotes that the 2000 observed land use was urban and the model predicted HDR. A value of 0 indicates accurate model performance in projecting the correct land use for that pixel in the year 2000 given 1980 inputs.

Tables 8 to 11 display model performance by error type in each of the subregion zones and the total domain for both the guided and blind simulations. The model performs best in the urban and rural zones compared to the suburban zone. Correctly projected pixels range from 55 percent to 57 percent in the urban and rural zones compared to only 30 percent to 31 percent in the suburban zone for both the guided and blind simulations. Overall model performance indicated a 56 percent to 57 percent accuracy in projecting the correct land use by pixel; however, there was only a very small increase in the number of correctly projected pixels between the guided and blind simulations.

The category of errors that impacted model performance varied significantly between the respective subregion zones. The urban zone was most influenced by error category -5, where the projected pixel should have been HDR and the model projected undeveloped land. For the rural zone, the most common error category was -4, which occurs when the model projects undeveloped land while the correct pixel was LDR. The suburban zone’s largest error also was the -4 category error, and significant category 2 error also was found where the projected pixel should have been LDR while the model projected HDR.

DISCUSSION AND CONCLUSIONS

We have presented the results of an effort to validate the performance of a spatial growth model in forecasting land-use change over a 20-year period. The basis for this evaluation was a comparison between a “blind” and a “guided” forecast and remotely sensed land-use map at the end of the 20-year projection period. The blind forecast was made with no foreknowledge of population and employment growth, using only trend estimates that would have been available at the beginning of the projection. On the other hand, the guided forecast utilized actual population and employment data over the projection period. As previously discussed, inaccuracies in the blind forecast may be attributed to errors in (1) model inputs such as population projections, (2) model parameters, (3) model formulation (growth rules), and (4) random errors. The guided forecast nearly eliminates errors of the first type and reduces errors of the second type, leaving types 3 and 4 as the predominant sources of forecast uncertainty.

An inconsistency between the 1980 and 2000 land-use classifications is likely impacting overall results. In 1980, the area coverage of HDR land use was estimated to be more than three times that of the LDR area, while in the year 2000 this relationship was reversed, with the LDR area nearly 60 percent greater than the HDR area. Such a dramatic change in the HDR/LDR ratio seems highly unlikely and is a probable source of error in HDR and LDR projections. Because the model uses the 1980 base map as a starting point and simply adds developed land to it, any errors in the initial states will translate into the projected land use. This inconsistency between the starting (1980) land-use base map and the 2000 base map complicates validation and contributes to the below-average model performance in predicting LDR development.

The blind forecast overestimates development of urban (commercial and industrial) land use and dramatically underestimates low-density residential development. New LDR growth is confined too tightly to the road network. Growth of high-density residential land use is well estimated in the blind forecast. The guided forecast somewhat overestimates urban growth and underestimates LDR growth, but not so badly as does the blind forecast.
HDR growth is very well simulated in the guided forecast. Spatially, the model is capturing the patterns of development desired for each of the developed classes. Kappa statistics and Moran's I autocorrelations indicate that model results for the urban commercial and HDR classes are good with values well above 0 for the Kappa statistics and autocorrelations around .90 for Moran's I. Results are not so good for the LDR class; however, the .79 Moran's I is very acceptable. The low Kappa statistic for LDR is influenced by the quantity error resulting in low quantities of land allocated for LDR. The Kappa statistic also may overestimate chance agreement at the expense of model performance or output accuracy. Pontius (2000) and others have argued that the Kappa statistic does not appropriately reward the model output or classification for accurate quantity estimates for each class. Nevertheless, the Kappa statistic in conjunction with Moran's I confirm that the rule-based aspect of the model that drives the spatial distribution of growth is performing well.

These results indicate that errors in population and employment forecasts have a substantial impact on the ability of a growth model to simulate urban land-use changes. Also affecting the model performance are the uncertainties in estimating model parameters such as dwelling units per acre and jobs per acre. Problems with forecasts and parameters are prominent in error types -4 and -5 that were evident in the subregion analysis, which underestimates LDR and HDR pixels respectively. The major overall error in the simulation is the underprojection of the number of pixels needed for LDR, which results in the model typically projecting too much undeveloped land. This result is captured in error category -4. The underforecasting of land needed for LDR is directly linked to the population forecasts and associated density assumptions made in the model inputs and parameters. Given accurate projections of population and employment, the agreement between observed and forecasted land use is quite good, and the spatial patterns of development are very realistic.

Finally, having GIS-based cost-effective dynamic models that allow the user to make adjustments to reflect the impact of faster or slower growth, different distributions of growth, and other factors that may impact the growth rate and dispersion of the population is critical. In that regard, the PSGM is advantageous compared to CA and other agent-based models, which require either the UNIX environment, a high number of simulations, a long run time, or a large amount of detailed spatial data (for example, raw land prices, construction costs).

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ParticipatoryGIS: A Web-based Collaborative GIS and Multicriteria Decision Analysis

Soheil Boroushaki and Jacek Malczewski

Abstract: This paper presents a framework for a collaborative WebGIS-multicriteria decision analysis. It focuses on the underlying theories and techniques for designing and implementing the conceptual framework. The framework, called ParticipatoryGIS, has been implemented within the Google Maps environment; it consists of two main elements supporting the deliberative and analytic components of the decision-making process. The deliberative part is based on the concept of Argumentation Maps; the analytic component consists of multicriteria decision analysis methods. ParticipatoryGIS uses the server-side architecture approach to Web-based GIS. It employs HTML, CSS, and JavaScript on the client side and a combination of PHP scripting language and a MySQL database on the ParticipatoryGIS server. The Google Maps server provides the map and Google Maps API.

INTRODUCTION

Citizens are increasingly demanding greater public participation in shaping public policy decisions that affect their lives. A variety of participatory procedures exist that aim at involving the public and integrating the local knowledge and preferences with the scientific inputs of the experts (e.g., planners) within the decision process (Dunn 2007, Rinner et al. 2008, Jankowski 2009). However, the capabilities of traditional methods of public participation and collaboration (e.g., public meetings) are limited because of their synchronous and place-based nature. The conventional models of public participation often have been criticized for their deficiencies in representing certain interest groups and local residents; it is because some individuals and groups cannot be present at a specific time and location, and may be reluctant to voice their preferences among other community members (Dragićević and Balram 2004, Jankowski 2009). To facilitate effective public participation, the spatial planning and decision-making procedures should be collaborative and distributed over an extended period of time (Carver and Peekham 1999, Jankowski and Nyerges 2001, Dragićević and Balram 2004).

The rapid improvement and innovation in the geographical information software and related computing hardware have made GIS the main tool for spatial planning and decision making. Nonetheless, the progress in using GIS to improve public collaboration in spatial decision making has been rather limited (Sieber 2006, Dunn 2007). While the planners and decision makers have full access to relevant spatial data/information, as well as to spatial planning tools such as GIS and related technologies, there are relatively few spatial planning and decision-making tools available to the general public (Pickles 1995, Carver 1999, Carver and Peekham 1999, Dragićević 2004). GIS typically has been a centralized, exclusionary, expensive, and technocratic tool requiring expert users to maintain effective and efficient operations (Dragićević 2004, Miller 2006). The system has been criticized as being an elitist technology that widens the gap between expert users and the general public when employed for planning and decision-making applications (Pickles 1995). The main challenges of GIS-based spatial decision-making applications reside in bridging this gap by providing a tool for enhancing public participation and addressing the issues of access and equity.

Implementing GIS within the World Wide Web environment and integrating its capabilities with multicriteria decision analysis (MCDA) methods can provide a mechanism for bridging the gap between the general public and experts. Web-based GIS (WebGIS) can offer solutions that are accessible to nonexperts; moreover, online tools, such as discussion forums, can provide an alternative to the traditional place-based planning (for example, public meetings/hearings and open houses) for they do not require in-person attendance. Ultimately, by operating on the Internet, the access to GIS is not restricted by time or location (Carver 1999, Jankowski and Nyerges 2001, Dragićević 2004, Dragićević and Balram 2004).

In addition, the integration of GIS and MCDA facilitates the participation decision-making process by allowing participants to explore different aspects of a decision problem and articulate their preferences (Carver 1999, Malczewski 2006a). MCDA provides a mechanism for expressing the participants’ preferences and objectives for generating a compromise solution. Furthermore, MCDA can offer a structured environment for investigating the intensity and sources of conflicts among different participants. It also can improve communication and understanding among multiple decision makers, which, in turn, pave the way for converging preferences and building a consensus in such a way that a minimum conflict solution can be generated (Feick and Hall 1999, Jankowski and Nyerges 2001, Malczewski 2006a, b).

Within this framework, the ultimate goal of the GIS-based multicriteria decision analysis (GIS-MCDA) procedures is to tackle two distinct aspects of spatial collaborative decision making and planning. The procedures attempt to address (1) the deliberative structure of spatial planning (by building a consensus among various decision makers and interest groups through organizing
and facilitating communication) and (2) the analytical structure of spatial decision making (by generating a compromise solution that best represents the preferences of all participants) (Malczewski 1996; Feick and Hall 1999, 2004; Malczewski 2006b; Jankowski and Nyerges 2001; Simão et al. 2009).


Most of the second-generation WebGIS-MCDA applications addressed the shortcomings of the analytical structure by providing more comprehensive and sophisticated analytical modules (Rinner and Malczewski 2002). However, technological and methodological deficiency still can be noted in those systems in contrast with the nature of collaborative spatial planning and decision making. The majority of recently developed WebGIS-MCDA systems—like their first-generation counterparts—are not responsive to the deliberative dimension of spatial decision making. Specifically, they lack the mechanism and implementation necessary to support discussion (Rinner and Malczewski 2002, Evans et al. 2004, Karnatak et al. 2007, Rao et al. 2007).

Moreover, many of the recent applications are based on commercial WebGIS packages such as ArcIMS (Dragićević and Balram 2004, Karnatak et al. 2007, Rao et al. 2007, Simão et al. 2009). Miller (2006) has questioned the degree to which a GIS can play a role in a participatory system if it is built based on expensive commercial software unavailable to most of the communities and interest groups. Although most of the nonprofit organizations in North America have had access to free or subsidized commercial GIS software such as the ESRI products, the vast majority of communities around the world (specifically in developing countries) cannot afford to obtain GIS software and/or they lack the required expertise to use them. Therefore, it is important to develop a collaborative WebGIS application based on an open source or free-to-use software (with no monetary cost for acquisition or licensing) using publicly available free geospatial data. In such a case, the constraint on developers and users of such systems will not be their financial capabilities but rather the limitations imposed by their willingness to participate, explore, and learn from these systems (Hall and Leahy 2006).

The launch of Google Maps service in 2005 brought countless opportunities for communities around the world to obtain free access to easy-to-use and browser-based Web mapping functionalities as well as high-quality geospatial data. The applications being built on top of the Google Maps (Google Maps mashups), which employ easy-to-use and customizable Application Programming Interface (API) in conjunction with a Web-based database management system, provide a free WebGIS capable of storing, representing, and analyzing geospatial data. Furthermore, these Google Maps mashups offer WebGIS that is widely available and accessible to the general public and non-GIS experts who can accordingly interact with and present their customized information in a user-friendly and familiar environment. Although other Open Source Web-based GIS systems such as the University of Minnesota MapServer (http://mapserver.org/) are free, because of the complex process of their customization, they require GIS experts with the knowledge of digital mapping, encoding, and transfer protocol (Miller 2006, Rinner et al. 2008). This makes Google Maps an excellent candidate to construct the groundwork of any collaborative WebGIS development.

The main objective of this paper is to present a Google Maps–based WebGIS framework and its implementation for collaborative multicriteria spatial decision making. The proposed framework integrates the deliberative and analytic dimensions of spatial decision making and planning. The remainder of this paper is organized as follows: The next section provides detailed background information. It first examines the synergetic capabilities of the integration of GIS and MCDA to tackle spatial planning problems; it then discusses the potentials of the Internet as a medium to facilitate asynchronous and distributed collaborative spatial decision making; and, finally, the section provides a review of ArgooMap prototype’s properties as a tool for spatially referenced communications that corresponds to the deliberative element of spatial planning and decision making. These elements are brought together in the section called “Conceptual Framework for a Collaborative WebGIS-MCDA,” which describes our conceptual framework for collaborative spatial multicriteria decision making. The section on implementing this framework explains system architecture and user interface design. The final section presents concluding remarks.

BACKGROUND

GIS-based Multicriteria Decision Analysis

GIS-based multicriteria decision analysis (GIS-MCDA) can be defined as a process that transforms and combines geographical data (map criteria) and value judgments (decision-makers’ preferences) to obtain relevant information for decision making (Eastmen et al. 1995, Malczewski 1999). The main rationale behind integrating GIS and MCDA is that these two distinct areas of research can complement each other. While GIS is commonly recognized as a powerful and integrated tool with unique capabilities for storing, manipulating, analyzing, and visualizing spatial data for decision
making, MCDA provides a rich collection of procedures and algorithms for structuring decision problems, designing, evaluating, and prioritizing alternative decisions. It is in the context of the synergetic capabilities of GIS and MCDA that one can see the benefits for advancing theoretical and applied research on the integration of GIS and MCDA (Malczewski 1999, 2006a).

The effort to integrate GIS and MCDA can be associated with the current proliferation stage of GIS development (Malczewski 2006a). During this phase, the systems have been evolving from a “close” or expert-oriented to an “open” user-oriented technology. This has stimulated a movement in the GIS community towards using this technology to democratize the decision-making process via public participation and collaboration. Malczewski (2006a) suggested that it is in the context of the debate on the interrelationship between “GIS and society” (Pickles 1995) that one can see the potential for constructing GIS-MCDA systems to enhance and facilitate collaborative decision making.

In a collaborative multicriteria decision-making setting, the GIS-MCDA procedures take the form of aggregating individual judgments into a group preference in such a way that the best compromise alternative can be identified (Malczewski 2006a, b). Accordingly, a collaborative decision analysis involves a two-stage procedure: (1) the MCDA decision rules (i.e., the decision rules for combining the criterion maps according to the individual decision maker’s preferences) and (2) the collective choice rules (the decision rules for aggregating individual preferences into a group preference).

GIS-MCDA can potentially enhance collaborative decision-making processes by providing a flexible problem-solving framework in which participants can explore, understand, and redefine a decision problem (Feick and Hall 1999, Jankowski and Nyerges 2001, Kyem 2004, Malczewski 2006a, b). MCDA approaches can integrate multiple views of decision problems. They improve communication and facilitate the process of building a consensus and reaching compromise solutions. GIS-MCDA can support the collaborative process by providing a tool for structuring decision problems and facilitating communication among decision makers (Malczewski 2006a, b).

**Web-based GIS-MCDA**

The World Wide Web or, more practically, the Internet (as a deployment and communication medium) has introduced new trends in the mapping and the democratization of spatial data and maps. Using the medium of the Internet, GIS systems can be developed to address the notions of democratization with respect to spatial data and decision-making processes, open accessibility, and an effective distribution of spatial information. In this setting, the public access to the planning process is enhanced and the technology contributes to greater participation in democratic procedures (Carver 1999, Carver and Peekham 1999, Dragičević 2004, Dragičević and Balram 2004, Miller 2006).

A WebGIS approach can generate a distributed and collaborative environment with continual time setting for mapping and decision making. Integrating MCDA methods into WebGIS (WebGIS-MCDA) can provide an interactive Web-based tool for users to explore digital maps and express their opinions about spatial decision problems. In addition, individuals uncomfortable with expressing their views in public can voice their opinions and preferences in a detached environment; consequently, a wider and more representative audience can be reached. Such accessibility means that WebGIS-MCDA systems have the potential to stimulate a “bottom-up” approach to spatial decision making by providing public access to the data and models. The WebGIS-MCDA framework allows participants to input their value judgments based on “different location–different time” dimensions of the spatial-temporal dimensionality of collaborative decision making (Jankowski et al. 1997). Consequently, the equity and access problems of the traditional decision-making process can be addressed. The equity issue is handled by a Web-wide distributed system design and the access problem can be addressed by embedding a collaborative mechanism within the structure of WebGIS (Carver 1999, Jankowski and Nyerges 2001, Dragičević 2004, Dragičević and Balram 2004, Malczewski 2006b).

**ArguMap: A Google Map–based Tool for Spatially Referenced Communication**

The Argumentation Map (Argumap) concept was proposed by Rinner (1999, 2001) to support geographically referenced discussions in GIS by providing visual access to public georeferenced debates in the planning domain. Argumaps are based on the combination of an online discussion forum and a Web-based GIS. They were developed as a method for structuring debates with spatial elements in asynchronous online discussions (Rinner 2001, Sidlar and Rinner 2007).

Keßler (2004) implemented an Argumentation Map prototype as a proof of concept using open-source software to fulfill the requirements for the Argumap concept and to minimize the development cost. This prototype of an Argumentation Map as a WebGIS was implemented using a Geo Tools Lite mapping tool kit, a custom-built Java Applet for a discussion forum, the MySQL database for storing users’ geographically referenced discussions, and the University of Minnesota MapServer providing background map layers (Keßler 2004, Sidlar and Rinner 2007).

The Argumap prototype has been used for tackling a number of spatial planning problems (Sidlar and Rinner 2007, Simão et al. 2009). However, there are some technological difficulties with using the Argumap prototype. The main shortcoming of the prototype is its implementation as a Java Applet that requires Java Virtual Machine to be first downloaded and set up on users’ machines, which, in turn, diminishes the efficiency of the system.

In addition, the complex procedure of customizing MapServer and Geo Tools Lite to create a WebGIS makes the development process difficult. These problems led Rinner et al. (2008) to develop ArgooMap—an implementation of the Argumentation Map concept using the Google Maps API. The main objective of the migration from Java Applet platform to Google Maps–based argumentation was to improve the usability of the prototype while
**Figure 1.** Conceptual framework for collaborative WebGIS-MCDA

**Figure 2.** System architecture of ParticipatoryGIS

**Figure 3.** Sections and workflow of ParticipatoryGIS Web site
cutting the development cost by using free-of-charge geospatial data and functionalities provided by Google Maps service. The ease of use is crucial for the success of such systems where the target group is the general public who are not familiar with GIS functionalities (Rinner et al. 2008).

Conceptual Framework for a Collaborative WebGIS-MCDA
GIS-MCDA methods provide a platform for handling different views and debates that revolve around the identification of elements of a complex decision problem, the organization of elements into a hierarchical structure, the exploration of relationships among components of the problem, and the stimulation of communication among participants (Feick and Hall 1999, Jankowski and Nyerges 2001, Malczewski 2006a, b). However, GIS-MCDA approaches traditionally have focused on the integration of GIS systems (desktop or Web-based) and MCDA algorithms that address the analytical aspect of such systems. On the other hand, although Argumentation Maps can visualize the alternative locations and the georeferenced discussions concerning different aspects of a spatial decision-making problem, they lack the evaluative capabilities for finding the compromise alternative. To this end, we suggest that the implementation of an Argumentation Maps concept within a WebGIS-MCDA would result in a spatial decision-making prototype capable of simultaneously addressing deliberative and analytical dimensions of spatial decision making in an asynchronous and distributed environment.

Figure 1 illustrates the proposed conceptual framework for a collaborative WebGIS-MCDA, called ParticipatoryGIS (see www.ParticipatoryGIS.com). It consists of two main elements of deliberation and analysis, both implemented within the Google Maps environment, which provides required geospatial data and GIS functionalities. The analytical part of the framework corresponds to the collaborative MCDA decision rule by employing an MCDA algorithm for individual decision making and a collective choice rule to generate the group solution (see the section “GIS-based Multicriteria Decision Analysis”). In ParticipatoryGIS, we utilized quantifier-guided ordered weighted averaging (OWA) (Yager 1997) and the fuzzy majority approach (Passi and Yager 2006) for the MCDA decision rule and collective choice rule, respectively. Finally, the conceptual framework includes the aggregation of ArgooMap representing the deliberative element of the framework with the collaborative MCDA decision rule, which yields a Web-based prototype capable of tackling both dimensions of spatial decision making and planning.

IMPLEMENTING THE FRAMEWORK
System Architecture
ParticipatoryGIS uses the server-side architecture approach to Web-based GIS (Rinner and Jankowski 2002). It employs HTML, CSS, and JavaScript on the client side and a combination of PHP scripting language and a MySQL database on the ParticipatoryGIS server. In addition, the Google Maps server provides the map and Google Maps API upon which the system has been built, and the users mostly rely on their functionalities (see Figure 2).

All the geographical data (e.g., coordinates) as well as the alphanumeric information used by both deliberative and analytical elements of the system are stored in a MySQL database on the ParticipatoryGIS server. The data and information required for the analytical component consist of (1) user registration information (this information is required for the deliberative part pertaining to user identification); (2) decision alternatives’ locations (coordinates and addresses); (3) evaluation criteria values for each alternative; (4) criteria weights according to each user’s preferences; (5) the final score and rank of each alternative according to each individual judgment; and (6) the score and rank of each alternative based on the majority of the participants representing the group preference. From the deliberative part, markers, discussion contributions, and the relationship between them also are stored in the database.

The system architecture for most of the client-server communications utilizes JavaScript as the client-side programming script and XML as the preferred format for data transfer. This combination, also known as AJAX, enables the Web implementation to have continuous and seamless interaction with the server without waiting for the whole Web page to be reloaded. AJAX technology enables the integration of analytical and deliberative parts (elements of the conceptual framework) in a single Web page with a set of tools and functionalities resembling a desktop GIS. The next section discusses the implementation of the user interface of ParticipatoryGIS.

User Interface Description
Figure 3 shows the workflow of ParticipatoryGIS. The workflow consists of three main sections: (1) registration and log in, (2) the main map, and (3) the questionnaire. The registration and log-in section consists of four pages: (1) log in, (2) user registration, (3) terms and conditions, and (4) an “About ParticipatoryGIS” section. Users accessing the Web site for the first time can register on the “User Registration” page. By completing the registration, users then are redirected to the “Tutorial” page. Upon registration, users have to read and agree to the terms of ParticipatoryGIS use, which are available on the “Terms and Conditions” page. Returning users can log into the system using the “Log In” index page on which they are redirected to the “Main Decision Map.” The “About ParticipatoryGIS” page introduces the design and development team. Figure 3 shows a basic flowchart illustrating site navigation.

The main map section of the system has been constructed using two Web pages: “Tutorial” and “Main Decision Map.” Tutorial describes the goal and objectives of the spatial decision problem at hand and provides a detailed explanation of the properties and geospatial characteristics of the decision alternatives.
Figure 4. Decision alternatives map layer of the main map page (screen shot from ParticipatoryGIS case study, town of Canmore, Alberta)

Figure 5. Individual decision map layer (screen shot from ParticipatoryGIS case study, town of Canmore, Alberta)
Figure 6. Group decision map layer (screen shot from ParticipatoryGIS case study, town of Canmore, Alberta)

Figure 7. Decision alternatives map layer and ArgooMap overlay within main decision map (screen shot from ParticipatoryGIS case study, town of Canmore, Alberta)
The definitions evaluation criteria and their units of measurement are given in the Tutorial page as well. In addition, it provides a step-by-step walk-through on how to use the Web site for selecting the preferred location, and how to participate in debates and communications with other users through the implemented ArgooMap. Within the Main Decision Map component, four map layers can be turned on and off using AJAX technology. The map layers are as follows: the decision alternatives map, the individual decision map and group decision map as part of the analytical element of the framework, and, finally, the ArgooMap layer representing the deliberative part of the conceptual framework (see the “Conceptual Framework” section).

The decision alternatives map shows the locations of the decision alternatives. By clicking on each alternative, a window will open that displays the corresponding properties and evaluation criteria values. This enables the users to browse and compare the characteristics of the alternatives (see Figure 4). The users then can input their preferences regarding the relative importance of each criterion using a set of linguistic terms. The set of six linguistic terms used in ParticipatoryGIS includes: none, very low, low, medium, high, and very high (Chen and Hwang 1992). In addition, users should choose a linguistic label to define how many of the evaluation criteria should be satisfied by an acceptable location. Then the linguistic label guides the OWA aggregation procedure, which generates the final score for each alternative. By submitting the user’s preferences, the individual decision map visualizes the rank of each alternative based on its OWA score (see Figure 5).

Within the Main Decision Map element, users can activate the group decision map. The group decision map displays the rank order for each alternative based on the majority preferences of the users (see Figure 6), while the alternatives’ scores in the group decision map layer are generated by the fuzzy majority procedure (Passi and Yager 2006). In addition, the users can activate or deactivate Argoomap as an overlay in conjunction with the analytical maps (shown in Figure 7). The Argoomap layer enables the participant to initiate a new georeferenced discussion or to reply to the already existing threads contributed by the other users. When the Argoomap is on, a user can select a reference location on the map to begin a new contribution to the discussion regarding the decision problem. The users also can have more than one reference point to start a discussion. When the Argoomap is on, the system reads all the discussion threads from the database and manifests them visually on the map using orange pins. By clicking on each pin, the users can read all the threads referenced to that location and also can begin a new discussion thread or reply to an already existing one. In addition, ParticipatoryGIS enables the participants to start a new thread or reply to one for discussion and debate on all the predefined alternative locations.

By saving the preferences, users then are redirected to the questionnaire form. The questionnaire facilitates the evaluation of the different aspects of the participants’ characteristics and provides data that can be used later for the usability evaluation of the system. The collected data and information within the questionnaire form include the participant’s age, gender, and education; prior experience with GIS, Internet, and participatory projects; and, finally, the degree of satisfaction with using ParticipatoryGIS.

**CONCLUSION**

The purpose of this paper was to describe the design of a novel conceptual framework for Web-based collaborative spatial decision making and its implementation in ParticipatoryGIS as a proof of concept. The framework integrates two prominent components of spatial decision making and planning—deliberation and analysis—in a cohesive fashion. The deliberative element of the prototype facilitates and encourages communication and debate among the decision makers and stakeholders, while the analytical structure provides procedures for identifying a compromise decision alternative.

We proposed to build the prototype using Google Maps service to gain access to the free-of-charge geospatial data and user-friendly environment. For the implementation of the framework, we used free scripting language, database, and map service that enhances the sustainability of the collaborative spatial decision-making projects. The main rationale behind collaborative MCDA is that the approach provides a mechanism for developing a constructive, creative, and transparent dialogue among stakeholders involved in the decision process rather than merely supporting them in the identification of the best alternative. In this context, we suggest that the concept of ParticipatoryGIS makes a considerable contribution to the area of collaborative MCDA by combining the deliberative and analytical dimension of decision-making processes.

Although, ParticipatoryGIS has been designed and implemented for the spatial multicriteria problems with predefined alternatives, the same prototype can be used through Argoomap for scenarios in which the alternatives are generated through public participation. The architecture of the prototype has been selected and implemented in a way that makes it a straightforward procedure to customize the system for different spatial decision problems. Our future research will be directed towards developing and implementing the architecture of a Web-based spatial multicriteria evaluation process that acts as a service rather than as a system. This architecture enables communities to define their own spatial decision problem and make it available online for public participation and input. Accordingly, rather than being a problem-specific system, the architecture will offer all the capabilities of ParticipatoryGIS for user-defined decision problems.

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TRADITIONAL GENETIC ALGORITHM AND RANDOM-WEIGHTED GENETIC ALGORITHM WITH GIS TO PLAN RADIO NETWORK

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Abstract: Cell planning as a process in GSM network planning must take into consideration all the criteria that are related to the cell-planning process, including the technical, financial, and environmental criteria. This paper aims to improve an integrated framework of cell planning that selects the optimal locations of base stations based on finding the trade-offs between coverage area, cost, and the health effects on the populations. The problem of base stations siting in this paper is reformulated from an unconstrained multiobjective optimization problem into a constrained multiobjective optimization problem. Two types of evolutionary algorithms, a traditional genetic algorithm with penalty functions as constraint handling and a random-weighted genetic algorithm (RWGA), were implemented and compared based on which one can produce an optimal solution in less iteration. The minimum number of base stations that are required to cover the conducted area was predicted based on the produced solution and was compared with the number of base stations that are constructed by the Mobinil operator. Cairo was selected as the conducted research area; both models were superior to the Mobinil scenario in covering the conducted area with a less number of base stations.

INTRODUCTION

In the GSM network planning process, base stations are considered the most important element in the entire network because of their role in physically connecting to mobile stations (users’ devices) through air interface (Ericson 2002, Nokia 2002, Mishra 2005, AirCom 2002); so the biggest problem in the planning process is where to locate those base stations appropriately to achieve the goals of service providers, including maximizing the coverage area and minimizing the construction and deployment cost (Raisanen 2006, Martin 2005). On the other hand, these base stations must be located following security and safety procedures that must prevent the citizens from suffering from the negative effects of these base stations (Gaber et al. 2009). In Egypt, the National Telecommunication Regulatory Agency (NTRA) (NTRA 2005) rolled out a protocol that governs the process of macro-cell construction to prevent the populations from the negative effects of the base stations. This protocol contains many restrictions on the process of locating base stations especially inside cities, such as the distance from the nearest school and hospital, the maximum permissible power, and other criteria to prevent human contact with the emitted radiations from base stations (Gaber et al. 2009).

Many approaches are proposed to solve the problem of base stations siting; these approaches can be classified into three categories: geometric, spatial decision support systems (SDSS), and mathematical (Gaber et al. 2009). In the geometric class, the researchers tried to build a geometric model that locates base stations to minimize the negative health effects (Zhang and Fan 2004) or to solve the problem of maximizing coverage/service in a certain area (Das et al. 2006, Roy et al. 2007). Cell planning using SDSS is another direction (Raisanen 2006, Martin 2005, Scheibe 2006). Finally, in the mathematical category, cell planning is considered an optimization problem and solved using a mathematical model such as the polynomial–time approximation scheme (PTAS) (Glaber et al. 2005).

Unlike the previous approaches, this paper incorporates all the factors that influence the base station siting, including cost, coverage area, and restrictions of public health. From the viewpoint of operation research, the problem of locating base stations is considered a constrained multiobjective optimization problem and can be solved using one of the famous evolutionary algorithms such as the genetic algorithms. In this paper, the base station locating problem will be solved in two ways using evolutionary algorithms. In the first algorithm, the objective functions will be aggregated to build a single combined objective function and then a traditional genetic algorithm will be incorporated with penalty functions as constraints handling (Schnier 2002, Montes and Coello 2006) to find the solution with a better fitness function value. On the other side, a random-weighted genetic algorithm will be used to find the nondominant individuals and the binary tournament selection method will be used to handle the constraints (Konak et al. 2006, Sáez-Sánchez et al. 2008).

A fully functional GIS is an integration of several components and different subsystems to collect, store, retrieve, and analyze spatially referenced data. GIS is a powerful tool of acquisition, management, and analysis of spatially referenced data, but GIS is a limited tool in a spatial decision-aid domain, because, essentially, it lacks more powerful analytical tools that enable it to deal with spatial problems involving several parties with conflicting objectives and criteria (Chakhar 2003).

To avoid GIS criticisms and to execute the spatial analysis on GIS data, integration between GIS and Operations Research/Management Science (OR/MS) tools is suggested. Practically, the idea of integrating GIS with several decision support systems (DSS) tools seems to be a long-term solution. In fact, this requires the development of a coherent theory of spatial analysis parallel to a theory of spatial data (Chakhar 2003). A more practical solution is to incorporate only chosen analytical methods into the GIS. This integration allows the user to benefit from GIS as a powerful tool for managing spatially referenced data and at the
same time from multicriteria analysis (MCA) as an efficient tool for modeling spatial problems. This paper uses multiobjective optimization (MOO) using genetic algorithms (GA) to find the optimal locations for base stations. An SDSS that integrates the multiobjective optimization technique with GIS is proposed. In this SDSS, basic GIS functions and the GA module is integrated and the GIS database is extended to support both the geographical, descriptive data of base stations and the GA model parameters.

**PROPOSED MODEL**

The criteria that will be used in the process of locating base stations can be classified into three categories: technical, economical, and environmental (Gaber et al. 2009). According to this classification, the service provider decides which location is proper based on technical and economical criteria, including maximizing the coverage area and minimizing the construction and deployment cost. On the other side, the NTRA and official authorities cannot grant permission unless the environmental criteria are satisfied; this category includes all the procedures that are stated in the NTRA protocols. These procedures include: must be located a specific distance from the nearest school, the occupied building must not be a hospital, and the transmitted power must not exceed the permissible power density.

The mathematical model of the base stations siting problem can be written as follows in equations (1-13) (assuming that all objectives are in minimization form):

\[
\begin{align*}
\text{Minimize } F(x) &= (f_1(x), f_2(x)) \\
f_1(x) &= \sum_{i=1}^{NBS} c_i x_i \\
f_2(x) &= \sum_{i=1}^{NBS} c_i x_i \\
\sum_{i=1}^{NBS} x_i &= NBS \\
\sum_{i=1}^{NBS} d_i x_i &= 0 \\
\sum_{i=1}^{NBS} h_i x_i &= 0 \\
\sum_{i=1}^{NBS} p_i x_i &\leq NBS p_c \\
x_i &\in \{0,1\} \text{ if BTS is located in ith location} \\
&= 0 \text{ if BTS is not located in ith location}
\end{align*}
\]

The \( i \) represents the \( i^{th} \) location from 1 to \( n^{th} \) location, \( c_i \) represents the total cost of construction and deployment of only one base station, \( c_{r_i} \) represents the coverage area of only one base station, \( x_i \) indicates if the base station is located in \( i^{th} \) location and takes the value 1 if the base station is allocated in \( i^{th} \) location; otherwise, it is 0. \( NBS \) represents the number of base stations that should be located, \( d_i \) represents the variable that indicates if the distance between the base station and the nearest school is less than or equal to 20 meters or not and takes the value 1 if this distance is less than or equal to 20 meters; otherwise, it is 0. The \( h_i \) represents the variable that indicates if the occupied building is a hospital or not and takes the value 1 if the occupied building is a hospital; otherwise, it takes 0. The \( p_i \) represents the transmitted power from the base station. Finally, \( p_c \) represents the maximum permissible power.

There are many input parameters, including \( h_i, d_i, p_i, c_i, \) and \( c_{r_i} \). And \( x_i \) in this case represents a decision variable that takes the value 0 or 1 to indicate if the base station is located in \( i^{th} \) location or not as follows:

\[
\begin{align*}
d_i &= 1 \text{ if distance from nearest school } \leq 20 \\
&= 0 \text{ otherwise} \\
h_i &= 1 \text{ if BTS is located on a hospital} \\
&= 0 \text{ otherwise} \\
p_i &\in \mathbb{R} \\
c_i &\in \mathbb{R} \\
c_{r_i} &\in \mathbb{R} \\
x_i &= 1 \text{ if BTS is located in ith location} \\
&= 0 \text{ if BTS is not located in ith location}
\end{align*}
\]

**System Overview**

The designed planning tool consists of the following components: Radio Wave Propagation module, comparison module, Coverage Area Builder, optimizer that essentially interacts with the genetic algorithm module to produce optimal solutions, and, finally, the GIS part, the user interface that allows the user to capture initial locations on the map and also display the results as points on the map. The Radio Wave Propagation module calculates the path loss using the Okumara Hata model (Catedra and Arriaga 1999) to compute the cell radios and then calculate the coverage area of the cell; these calculations are described in detail in our previous paper (Gaber et al. 2009).

The Coverage Area Builder takes the optimal points from the optimizer and, based on the locations of these points, predicts the locations of the rest points that are required to cover the whole conducted area in the geometric process. After predicting the whole coverage area and the locations of all the points, these points are compared with the existing locations of one of the running operators (in this case, the Mobinil operator is chosen for comparison) and, finally, the results of the comparison are displayed. The resultant points are displayed on the map as separate layers to deal with them in the remaining steps of the planning process. This paper will focus in the next sections on applying more than the genetic algorithm to optimize the chosen locations, with comparisons between those algorithms and Mobinil points. Two algorithms are used in this paper: a traditional genetic algorithm

![Radio network planning tool architecture](image-url)
with penalty function and a random-weighted genetic algorithm with a binary selection scheme.

Traditional Genetic Algorithm with Penalty Function

Traditional genetic algorithms are proposed to deal with single objective problems and usually produce only one solution that has the better fitness value (Konak et al. 2006, Amin 2007, Coley 2001). In this paper, a multiobjective optimization problem is transformed into a single objective optimization problem by aggregating the multiple objectives. A penalty function that penalizes the infeasible solutions to pose the feasible ones to be selected (Schnier 2002, Montes and Coello 2006, Coello 1999) also is applied to deal with the constraints that restrict locating the base station. The candidate solution can be evaluated by calculating the cost and coverage area objective function of locating base stations as in equation (14):

\[ f(x) = \sum_{i=1}^{n} (C_i x_i - cr x_i) \quad (14) \]

The infeasible solutions can be penalized by calculating the constraints that restrict the process of base station siting for each solution. The constraint violation (V) is calculated as follows in equation (15):

\[ V(X_i) = \max(0, Gi(X_i)) \quad (15) \]

Then all constraint violations of a chromosome (with n solutions) are added together to find the overall constraint violations as in equation (16):

\[ \text{total\_violate} = \sum_{i=1}^{n} V(X_i) \quad (16) \]

After that, the total constraint violations are added to the fitness function of the chromosome as in equation (17):

\[ F_p = f(x) + \text{total\_violate} \quad (17) \]

In the traditional genetic algorithm with penalty function, a binary coding is used (Gaber et al. 2009, Amin 2007) with a chromosome equal to the number of predefined locations that are captured using the GIS component. For example, a solution that consists of five genes as 1-0-1-0-0 denotes that only locations 1 and 3 will be chosen to construct base stations. Roulette-wheel selection, single-point crossover, and binary mutation are applied to select the parents and generate new offspring (Gaber et al. 2009). To deal with the restriction of determining the number of base stations in any solution equal to a prespecified number, the Restricted Search Operator is used. The Restricted Search Operator initiated by Salcedo-Sanz in 2004 (Salcedo-Sanz et al. 2008) is shown in Figure 2:

Random-weighted Genetic Algorithm (RWGA)

The random-weighted genetic algorithm (Konak et al. 2006), initially proposed by Murata and Ishibuchi in 1996, uses the weights to build an objective function. The weights are changed frequently during the running time to allow the searching directions to be changed to sweep over the entire solution space. To perform this task, random numbers are generated to build the weights of the individuals and then the solutions that are found through changing directions are collected in a set to build the Pareto optimal set (Konak et al. 2006).

Initial solutions are randomly chosen using the GIS component and transferred to the optimizer to encode them as the initial population. Then the objective values of the chromosomes in the population are calculated and the Pareto optimal solutions are recorded. The total objective function is composed of the linear combination of the objective functions. And the weights are randomly assigned. For a solution x, the objective function in the study is represented as follows in equation (18):

\[ f(x) = w_1 f_1(x) + w_2 f_2(x) \quad (18) \]

Where \( f_1 \) and \( f_2 \) are objective functions, they denote the cost and the coverage area of the base station, respectively. And \( w_1 \) and \( w_2 \) are computed randomly during running time as in equation (19):

\[ w_k = \frac{u_k}{\sum_{k=1}^{n} u_k} \quad (19) \]

Where \( u_k \) is the random number generated between [0,1].

In RWGA, the selection probability can be used to select the parents with high probabilities instead of using the original concept of fitness (the larger the better) because solutions with larger fitness tend to propagate to the next generation in order to allow this algorithm to select the solutions with minimum fitness value where minimization form is applied in this algorithm. The selection probability can be formulated as in equation (20):

\[ p(x) = f(x) - f(x) (\sum y \in y_p (f(x) - f(y)))^{-1} \quad (20) \]
The binary tournament selection method is applied in RWGA as shown in Figure 3.

Like a traditional genetic algorithm, single-point crossover and bit flop as mutation techniques are applied. To maintain the elite solution during the running of the algorithm inside the external population, an elitism strategy (Konak et al. 2006) checks if the member already exists in the external population or not. If the population doesn’t contain this member, then the member is added. If the size of the external population exceeds the predefined size, then the elitism strategy will check if the member is nondominant according to the members of the external population and replaces the dominated member by the new nondominant member.

The new population is generated by deleting the number of individuals equal to the size of the Pareto optimal set and adding the same number of solutions from the external archive to the population. Then the Pareto optimal solutions are updated. If the number of generations reaches a prespecified number (entered by user), then the process must be terminated; otherwise, evaluate the population and apply the algorithm again. RWGA is summarized as follows (Konak et al. 2006):

**Step 1**: Randomly choose two solutions \( x \) and \( y \) from the population.

**Step 2**: If one of the solutions is infeasible and the other one is feasible, the winner is the feasible solution, and stop.

Otherwise, if both solutions are infeasible, go to **Step 3**, else go to **Step 4**.

**Step 3**: In this case, solutions \( x \) and \( y \) are both infeasible. Then, calculate a measure of infeasibility \( C(x) \), the number of constraints violated or total constraint violation for solutions \( x \) and \( y \) and the solution with the least infeasibility could be declared as the winner.

**Step 4**: In the case that solutions \( x \) and \( y \) are both feasible, if one of them dominates the other then the winner one is the non-dominant.

![Figure 3. Modified binary selection strategy in RWGA](image)

**Step 1**: Generate a random population.

**Step 2**: Assign a fitness value to each solution \( x \in P \), by performing the following steps:

**Step 2.1**: Generate a random number \( q_k \) in \([0,1]\) for each objective \( k = 1, \ldots, K \).

**Step 2.2**: Calculate the random weight of each objective \( k \) as:

**Step 2.3**: Calculate the fitness of the solution as:

**Step 3**: Calculate the selection probability of each solution \( x \in P \) as follows:

**Step 4**: Select parents using the selection probabilities calculated in **Step 3**. Apply crossover on the selected parent pairs to create \( N \) offspring. Mutate offspring with a predefined mutation rate. Copy all offspring to \( P_{t+1} \). Update \( E \) if necessary.

**Step 5**: Randomly remove \( n_E \) solutions from \( P_{t+1} \) and add the same number of solutions from \( E \) to \( P_{t+1} \).

**Step 6**: If the stopping condition is not satisfied, set \( t = t+1 \) and go to **Step 2**. Otherwise, return to **E**.

![Figure 4. Random-weighted genetic algorithm](image)

**EXPERIMENTAL RESULTS**

This model is conducted in Cairo to compare the locations of antennas that are produced from both traditional genetic algorithm and random-weighted genetic algorithm models to the already existing locations that are constructed by the Mobinil operator. From the literature, the feasible values that will produce relatively good solutions are recorded as the crossover/recombination probability equals 0.9 and the mutation probability equals 0.1 (Martin 2005).

To test traditional genetic algorithms and random-weighted genetic algorithms for the problem of base station siting, testing data that are already known and can be used to easily determine the optimal solution is produced for the purpose of testing. And the optimal solution is extracted manually to compare it with the produced solutions from both models to compare the effectiveness of those models. Figure 5.a explains these data and indicates the optimal solution that is produced manually as the solution that has a maximum coverage area and a minimum cost and can be shown at the end of the test data. These locations are divided into four initial solutions that will be used as the initial population to carry out the models as shown in Figure 5.b. Figure 5.c shows that RWGA was able to find the optimal solution after only 100 iterations, while the traditional genetic algorithm found the optimal solution after 150 iterations. So RWGA converges to optimality faster than does traditional genetic algorithms. This behavior can be interpreted by the nature of the RWGA that uses random weights to search the solutions space in many directions and also by the ability of the RWGA to find the nondominated solutions over a vector of objectives rather than a single objective and maintain an elite solution that is nondominated by others. The nondominance principle allows the model to search in more than one direction simultaneously.

Traditional genetic algorithms and RWGA were used to find the optimal solution for the base station siting problem. Real data were collected by building four scenarios to construct base stations on different locations inside Cairo. These data were divided into four solutions, each solution containing a set of locations. Optimization models were carried out on these data to produce an optimal solution that will be used as a basis to predict the number of base stations that are needed to entirely cover Cairo. Mobinil data about the existing base stations also was collected to compare the produced solution from each model with Mobinil data. Figure 6.a shows the real data that were collected to carry out the optimization model. A traditional genetic algorithm and a RWGA...
**Figure 5.** Test data, their distribution, and convergence

- **a. Test Data**
  - | Location_ID | Coverage Area | Cost |
  - |---|---|---|
  - | 1 | 0.1 | 0.55 |
  - | 2 | 0.5 | 0.5 |
  - | 3 | 1 | 0.47 |
  - | 4 | 1.5 | 0.45 |
  - | 5 | 2 | 0.4 |
  - | 6 | 2.5 | 0.38 |
  - | 7 | 3 | 0.37 |
  - | 8 | 3.5 | 0.35 |
  - | 9 | 4 | 0.3 |
  - | 10 | 4.5 | 0.25 |
  - | 11 | 5 | 0.2 |
  - | 12 | 5.5 | 0.14 |
  - | 13 | 6 | 0.1 |
  - | 14 | 6.5 | 0.06 |
  - | 15 | 7 | 0.04 |
  - | 16 | 7.5 | 0.02 |

- **b. Distribution of locations on the initial solutions**
  - | No. of Iterations | RWGA | Traditional GA |
  - |---|---|---|
  - | 10 | 9,10,13,14 | 11,12,13,16 |
  - | 20 | 12,13,14,15 | 10,12,13,16 |
  - | 50 | 12,14,15,16 | 11,13,15,16 |
  - | 100 | 13,14,15,16 | 11,14,15,16 |
  - | 150 | 13,14,15,16 | 11,14,15,16 |

- **c. Convergence of RWGA and Traditional GA**

**Figure 6.** Collected real data

- **a. 16 locations captured from GIS Component**
  - | Location_ID | X | Y | Cov_area | Cost |
  - |---|---|---|---|---|
  - | 1 | 338497 | 3334280 | 0.29 | 2.1 |
  - | 2 | 340990 | 3325539 | 0.49 | 2.6 |
  - | 3 | 330663 | 3324823 | 2.29 | 3.2 |
  - | 4 | 326417 | 3329279 | 0.72 | 2.4 |
  - | 5 | 327882 | 3322899 | 5.28 | 3.52 |
  - | 6 | 327311 | 3320237 | 0.58 | 1.92 |
  - | 7 | 320153 | 3319423 | 0.63 | 2.0 |
  - | 8 | 328054 | 3314861 | 0.97 | 2.7 |
  - | 9 | 347140 | 3318551 | 1.28 | 3.42 |
  - | 10 | 320447 | 3317351 | 0.30 | 1.7 |
  - | 11 | 329279 | 3337046 | 3.74 | 1.2 |
  - | 12 | 338050 | 3302261 | 4.66 | 2.98 |
  - | 13 | 317627 | 3317828 | 0.40 | 3.12 |
  - | 14 | 320178 | 3342269 | 0.48 | 3.32 |
  - | 15 | 341606 | 3341959 | 0.65 | 2.1 |
  - | 16 | 328476 | 3326887 | 0.58 | 1.82 |

- **b. Results from Traditional GA and RWGA**
  - | Founded Solution | Traditional GA | RWGA |
  - |---|---|---|
  - | 5,11,12,16 | 5,10,11,16 |

- **c. Comparisons of GA models with Mobinil points**
  - | No. of Antennas | Traditional GA | RWGA | Mobinil |
  - |---|---|---|---|
  - | 224 | 201 | 236 |
were applied to these data and the results were recorded in Figure 6.b, which indicates that RWGA outperforms the traditional genetic algorithm by finding the solution that is able to build the whole coverage with a minimum number of base stations.

Some assumptions are made in this model; one of these assumptions is that all cells have the same radius. In the stage of comparison, 900 meters as a radius for all cells is assumed. As explained in Figure 6.c, the traditional genetic algorithm model succeeds in covering Cairo with 224 antennas, while RWGA covers Cairo with only 201 antennas. Both models are superior to the Mobinil scenario, which built 236 antennas but does not entirely cover Cairo so that the network still is incomplete. The number of identical points indicates the number of points that has the same coordinates with those in the Mobinil network. As shown in Figure 6, RWGA is more suitable because of its acceptable results.

CONCLUSION AND FUTURE WORK

The primary goal of this paper was to build GIS-based decision support systems that optimize the process of base stations siting in radio network planning. Many algorithms are proposed to automate radio network planning, but they ignore the health effects of antennas and how to avoid these negative effects; for this reason, this paper developed a model that takes into consideration all the criteria that are related to radio network planning. Two types of genetic algorithms are proposed in this paper, traditional genetic algorithms and random-weighted genetic algorithms. During the testing phase, the RWGA was able to find relatively good solutions faster than the traditional model did; both of them succeeded in covering the conducted area with less number of points than the Mobinil operator. Automated GSM network planning tools like this model make it possible for GSM operators to build an overall picture of a coverage area and where to locate their antennas, taking into consideration all the related criteria. These tools also can be used as testing tools for official bodies to make sure that the network conforms to the specifications according to NTRA protocols in Egypt.

The paper has highlighted several areas that warrant further investigation. First, it would be interesting to build a digital elevation model (DEM) for the conducted area to obtain the heights of buildings and the building specifications according to the siting protocols of the NTRA. This DEM then can be used to confirm the calculation of radio wave propagation to build an accurate power budget model. Second, other optimization models such as Tabu Search can be applied and the model expanded to investigate the process of Radio Network Optimization. Third, this model can be expanded to include the core network and how to integrate the planning process of radio and core networks into a single planning tool.

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About GeoLynx DMS:

Building and maintaining GIS data for public safety is easy with GeoComm’s E9-1-1 GIS data management software. GeoLynx DMS adds a toolbar to ESRI’s ArcMap that exposes features and functions specific to maintaining public safety GIS data that are not present in the standard ArcGIS product from ESRI: address assignment, address range creation, wireless cell sector maintenance, atlas generation, MSAG and CAD geofile management, and a broad range of quality assurance and quality control (QA/QC) audits.

Midland Emergency Communications District is relieved to be using GeoLynx DMS.

GeoLynx DMS is simple to use, once Vonda Gafford realized this was true, her work immediately improved and GIS data updates are provided more frequently to the PSAPs.

"I know where my data is, I know where my edits are going and I do not have to search for linking tables to make sure every aspect was modified. Basically, what you see is what you get," Gafford said.

Whether editing existing data, creating new data, importing or exporting data, Midland GIS staff is confident in the accuracy and quality of their GIS data.

Midland is seeing other benefits too such as being able to bring in data from other agencies and easily mesh it with their public safety GIS data. Using the quality control audits in GeoLynx DMS, Midland is assured that after merging data from other agencies or departments their data is clean and ready for use.

The time saved by using GeoLynx DMS can now be spent on other projects that time did not allow before.

"I am now able to get work done more efficiently and save money at the same time!" Gafford stated. "I am also very pleased with all calls made to GeoComm’s technical support. Everyone is very helpful and knowledgeable. Software upgrades and the support I have received when installing the upgrades has been amazing."
INTRODUCTION

In recent years, online geospatial systems for people who are not experts in the domain of spatial information science have emerged. For many of these systems, however, the data representation and the way of interacting with this data were inspired by systems that were created for expert users such as ArcGis, MapInfo, or Manifold.

The usability of these expert systems has been evaluated and criticized by several groups of researchers (Traynor and Williams 1995), but few researchers have yet explored whether data representation and interaction manners, taken from expert systems, are applicable to spatial information systems that are not used by experts.

Despite the fact that most major online Web-mapping systems such as Google Maps or Microsoft Live Search have been significantly improved regarding their usability, systems implemented for specific groups of users still lack such improvements. One reason for this problem might be that many of these systems are based on components that already have predefined interaction manners built in and that only offer a certain set of possibilities for data representation. Another reason is that, up until now, almost no specific usability guidelines exist for online geospatial systems that are built for specific groups of users such as real-world communities (Haklay and Zafiri 2008).

Usability engineering as a field within human-computer interaction was founded in the 1980s and has become a well-established discipline since then, yet we argue that usability testing for geospatial systems is different from usability testing of other software applications. The difference is rooted in the fact that both the data displayed in a geospatial system and the interface that allows for spatial interaction are particular: The spatial information that a user is interacting with is an abstract depiction of the real world; the user needs to match this abstract depiction with his or her internal, cognitive map to understand it. Moreover, the interface that allows for interacting with spatial information (e.g., spatial navigation or adding spatial information) should take into account the relationship with the interaction with the real world. These facts stress the importance of both a geospatial system’s interface and the depiction of the data itself. Therefore, the usability testing of geospatial systems includes not only the testing of an interface according to common usability measures (such as task completion time or errors), but implicates a deeper understanding of the interaction and the user.

Systems for real-world communities especially are an important research subject and challenge for geospatial science. Furthermore, this field of research needs to be addressed with evaluations involving members of the real-world community rather than with theoretical concepts (Jankowski and Nyerges 2003). Actual evaluations are necessary to find a methodology that proves to work for real-world communities.

Systems implemented for specific groups of users do only as much or as little as they are designed for. Yet each user perceives and uses them differently. These differences depend on several factors, such as specific interface features and previous knowledge and experience. Previous knowledge and experience particularly are reasons why it is important to take user context into account before, during, and after the implementation of a system.

In this paper, we describe the first phase of a research program aimed at responding to these immediate and larger challenges for GIScience and their relationship with nonexpert users as new modes of interaction become possible through new software tools.

To start making progress in a concrete and meaningful way, this research phase focused on a specific real-world application concerning a community of winegrowers in the Swiss canton of Vaud. Responding to spatial knowledge acquisition and spatial
planning needs, a Web-delivered geospatial information tool was deployed and evaluated.

We provide the context of this case study and explain the main challenges and needs of the users and how the project can help this real-world community. We identify the main hypotheses and research questions, explain the methods used, what the users' activities were during evaluation, and identify the relevance of these activities to the immediate case study and larger challenges for interactive nonexpert geospatial information tools. Finally, we present the results and conclude with a discussion about the results and their validity and in which direction further research should be driven.

Case Study Context

The context of the case study described in this paper is a system called RIV (réseau interactif en viticulture—interactive network for wine cultivation). RIV is a system targeted for different aspects involved in winegrowing and wine making in Switzerland. It focuses on the spatial aspects of winegrowing (e.g., the location of the parcels (the smallest spatial winegrowing entities), the existing microclimate, the type of soil, etc.) and it is entirely accessible through the Internet.

Wine making in Switzerland usually is on a very small scale (compared to countries such as France or Australia); many winegrowers have only one or two small parcels and they deliver their harvest to small local wine cellars where the wine is made.

Winegrowers are a rather heterogeneous group of users; many winegrowers grow wine as a part-time business. To survive, various winegrowers do have second businesses such as farming or even nonagriculture-related occupations. As a result, numerous users only have a few parcels.

Approximately 7,800 winegrowers are in the Swiss canton of Vaud where RIV was developed and released, according to the winegrowers’ association’s Web site, and most of them are potential users.

The main idea in creating RIV was developed from a previous project where maps of the microclimate and the soils in the region had been gathered (the “terroir-project,” Pythoud and Caloz 2001). At the end of the project, CDs containing static maps in PDF format were sent to the stakeholders. These maps were useful for the participants in the project. However, they did not reach all the winegrowers in the region, and there was no possibility to update those maps or to correlate the information in an interactive way.

A second reason to create RIV was an identified need to develop a tool to help winegrowers manage their parcels by “virtually” assembling parcels and correlating maps from the terroir project with their parcels. To use the system for parcel management, however, the users first have to digitize their parcels on top of aerial photos (with the support of the official cadastre).

RIV was conceived and developed in close collaboration with end users of the system in different cycles, following a user-centered system development approach (Preece et al. 2002). Several prototypes and mock-ups were developed (Ingensand 2006) and showed to end users to make sure that the system met their needs and requirements.

How Can Interactive Tools Help Real-world Communities?

Interactive spatial tools that are conceived and implemented for the public are a rather new phenomenon. Both the availability of spatial data and the increasing possibilities of Internet mapping systems have accelerated this process.

All these systems, however, were developed for unspecified groups of users and thus address as many users as possible. In most cases, the user can choose between different systems and select the one that corresponds best to his or her needs. With specific groups of users (such as the winegrowers in the canton of Vaud), the users' needs and competencies differ from those of the public. Therefore, such systems have to be adapted to their context.

Interactive spatial tools that are tailored to specific needs and competencies can help increase knowledge and also productivity. Groups that are working within a field with a strong connection to land, soil, and climate especially can benefit from such tools through an increased knowledge of their spatial context.

The challenge of developing tools for such groups of users lies not only in the development of the tool itself but also in the acquisition and the preparation of data. Yet the act of collecting spatial data that is adapted to a specific group is a task that can take much time and can be rather expensive. A solution to this problem, used within the context of this case study, is to let the users of this system collect their own spatial data.

To validate any development that has been created for specific groups of users, we need to develop a methodology that helps detect exactly how the users are interacting with such systems.

Hypotheses and Research Questions

In this evaluation, we wanted to emphasize questions and hypotheses that will be discussed and validated through the analysis of the tasks the users had to carry out with the system. However, the analysis of the system's overall efficiency and effectiveness also played an important role. These hypotheses are essential issues when evaluating the usability of any interface that represents and interacts with spatial data. Moreover, these hypotheses are also a fundamental part of our question if interactive Web-mapping systems can improve spatial consensus and awareness in real-world community applications.

In our hypotheses, we first analyze user performance. As user performance, we consider measures that are counts of actions and behavior that one can see (Dumas and Redish 1999).

User Behavior/Interface Use Influences

User behavior/ interface use significantly influences performance.

• Is it possible to identify different user strategies to solve specific tasks?
• Which strategies result in better performance?
• Is there an identifiable connection between the user’s performance and the user’s satisfaction?

Specific Interface Features Influence
Specific interface features significantly influence performance.
• Is there any evidence that some interface features cause a higher cognitive load?
• Were there differences in performance that were associated with features of RIV that are common with conventional GIS versus less conventional/interactive tools?

User Experience and Training Influences
User experience and training significantly influence performance.
• Are there identifiable differences between users?
• Is there any evidence to suggest that the user’s geospatial technology expertise has an influence on the user’s performance and the way the user interacted with the interface?

EVALUATION SETTING

To engage our hypotheses, we planned the evaluation in three parts:
• A questionnaire about the user’s education, background, and computer habits;
• The hands-on evaluation; and
• A second questionnaire concerning the usability of the system.

Besides the questions about the user’s background, the first questionnaire also contained some questions about the user’s experience with other geospatial systems (such as address-finding systems and three-dimensional visualization software).

We conducted the evaluation according to the think-aloud method (also known as verbal protocols) (Ericsson and Simon 1993). Users were encouraged to say what they think, feel, and do. The advantage of this method is that the evaluator receives much qualitative feedback that otherwise would have been uncovered in addition to the quantifiable feedback (Beer et al. 1997). The disadvantage of this method is that it takes more time; furthermore, Jacobsen et al. (1998) have described that the evaluation expert also exerts an influence on the outcome of the evaluation.

USER SELECTION

Users were selected using a database that was offered by the winegrowers’ association. All winegrowers who were listed with e-mail addresses in the database were selected as potential test persons (175 people). One hundred of these 175 winegrowers were selected, together with a representative of the winegrowers’ association. The invitations were sent in two series (50 and 50) with two months in between. For each of the series, ten winegrowers were ready to evaluate the system. The average age of these users was around 45 years (three winegrowers did not want to reveal their ages).

USER ACTIVITIES

The evaluations took place in an office at EPFL. Two persons—the evaluation expert and the evaluator (the user)—participated at each evaluation.

As mentioned previously, the second part of the evaluation was the actual interaction with the system. The evaluator received a set of tasks that he or she had to solve using the system. All tasks had been discussed with experts in the domain prior to the evaluation to make sure that the proposed scenario reflected the user’s common work tasks.

The tasks that had to be solved with the system were:
• Create one parcel on top of aerial images.
• Create at least one more.
• Display one’s parcels on a map.
• Display a map of the parcels and the soils.
• Navigate to the Vully region.
• Navigate to one’s village.
• Display different layers on the map (the user has the choice between a variety of different layers or some predefined compositions of layers).
• Select parcels on the map and save the selection.
• Find parcels at a specific altitude.
• Find parcels located on lime-containing soil.

For each task, the evaluator had to specify the level of difficulty on a scale from 1 to 5. Throughout the second part, the user was encouraged to speak aloud about what he or she was thinking and what he or she was trying to do. The evaluation expert only helped in cases where the evaluator did not manage to solve a task within approximately three minutes.

ANALYTICAL METHODS

To determine what occurred during the evaluation and also to find an ideal way to determine how the system was used in practice, we developed a methodology that captured as much of the user’s physical interaction with the system as possible and also what the user thought and said.

One point of departure for measuring the user’s interaction with the system was Aoidh and Bertolotto’s (2007) methodology of analyzing the spatial location of the user’s mouse interactions where the mouse’s spatial location is considered representative of the user’s interest in a specific feature. However, because RIV is a system with several menus, tools, and features, it was difficult to apply the same methodology to our evaluations. Another example was Tulis et al.’s (2002) comparison of lab and remote testing.
where a specifically instrumented browser was used for capturing the user’s interactions with the interaction of a Web site.

During the hands-on evaluation, different items were captured:

- The user through a video camera placed in front of the user (capturing sound and video);
- The user’s screen (through a desktop streaming tool);
- The evaluation expert’s notes; and
- The user’s interaction with the system in a log file on the server.

Our system uses Apache as a Web server that logs each user activity into a log file. To analyze the log file, we created a tool that parses the log file and puts it into a database with every column showing a parameter. Thereafter, we created a tool that extracts the information from the database and visualizes the whole interaction session with one specific user and the system (see Figure 1). The different parameters were translated into a more human-readable format, filtering unnecessary elements and emphasizing important elements:

- The time when the interaction occurred (with an absolute time stamp and relative time stamp to analyze the log file afterwards in synchronization with the recorded screen and video);
- What tools the user was using (e.g., zoom-in, recentering);
- What layers the user was requesting;
- If there were gaps of more than ten seconds in between the different queries.

For streaming the user’s desktop, we installed a VNC server on the evaluation computer that can be used for remotely controlling the computer. The signal of this VNC server is able to send the remote computer’s screen to a client, but also accepts user input from the client computer’s VNC client. For our evaluation, we used a tool installed on a second computer that streams this signal directly to a video file.

Before we used our log file visualization tool for measuring the user’s performance, we verified its functionality with the screen captures that had been recorded during each session. Moreover, we used the gap detection feature together with the videos (the user’s screen and the user) to determine what was happening when the user was hesitating at a specific moment.

RESULTS

We structured our results according to the hypotheses and research questions mentioned previously. For each research question, we tried to find evidence in the data we collected during the evaluations.

USER BEHAVIOR/INTERFACE USE INFLUENCES

Is it possible to identify different user strategies to solve specific tasks?

To respond to the first research question, we analyzed the first task—to navigate the system’s maps, to find the right spot, and then to digitize a parcel. We considered map navigation and digitization separately.

In RIV, the user had the choice of five different navigation tools (see Figure 2). Three navigation tools (zoom-in, zoom-out, and pan (to move the map)) where the selected tool is marked by...
a red frame, the scale choice list with 16 scales, and a menu that lets the user choose growing regions and villages. To analyze the user’s strategies in the first task we verified:

• How many “navigation clicks” the user made and
• What type of clicks the user made.

At first, some differences in the frequency of use of the different tools was noticed (see Figure 3):

• One out of 20 users tried out all the tools during the first task.
• Six users used four different tools.
• Seven users used three different tools.
• Six users managed to navigate to the right spot (where the parcel had to be digitized) with only two different navigation tools.
• Eight users clearly used the pair zoom-in/zoom-out for changing the scale (however, some tried other methods as well).
• Five users used the scale choice list at least as often as the zoom-in/zoom-out pair.

Furthermore, users who used only a few navigation tools also needed only a few navigation clicks to complete the first task. On the other hand, users who used many different navigation tools also made many clicks.

In ten cases, we noticed that users tried to click on the zoom tools and expected the system to zoom in. Eight of those ten users found out later that it is necessary to click on the map to zoom in or zoom out and two users tried other navigation tools (such as the scale choice list and the recenter tool).

During the first evaluation series, all users had problems digitizing the first parcel (it took at least two and at most six attempts to digitize it correctly). The ten users of this first series had some problems in common:

• Five users tried to digitize the parcel as they would draw a line on a map by holding the mouse button clicked.
• Three users drew a complex polygon instead of following the outer border of the object.
• Two users tried to “paint” the parcel’s interior with the digitization tool.

Because of this first result, the development team decided to help the user with that functionality and followed the suggestion of one of the first ten users to write a small note on the page (actually taken from the help pages) directing: (1) To zoom to the right place, (2) to select the digitizing tool, (3) to define the outer line of the parcel by clicking on the outer points, and (4) to click on the validation button once the parcel was finished. During the second evaluation series, six users managed to digitize the parcel.
at the first attempt; at most, it took three attempts to digitize it.

In the following tasks, we found no particular differences in the users' strategies compared to the first task. Here we were able to identify different user strategies for the interaction with the maps.

**Which strategies result in better performance?**
To analyze each user's performance during the first task, we measured:
- How much time each task took;
- Gaps of more than ten seconds between the user's clicks; and
- The number and type of errors the user made.

Navigation, the first subtask, is a continuing process where the user is:
- Considering the map and trying to put it into relation with the real world;
- Finding a strategy to change the state of the map (e.g., the map is not the right scale or is not showing the right place);
- Applying the strategy (zooming, recentering);
- Reconsidering the map, etc.

Measuring navigation time was difficult, however, because this evaluation was using verbal protocols—the user was encouraged to talk aloud while interacting with the system—thus gaps in the interaction with the system were quite frequent.

Because of these reasons, we decided to measure navigation time as follows:
- A navigation flow (many navigation clicks in a row) has less than ten seconds in between the navigation clicks; we counted the time from the beginning of the flow until the end of the flow;
- Single clicks with at least ten seconds in between.

For all users, we accumulated navigation flows and single clicks to one measure. We also counted the gap time separately.

Concerning different navigation strategies, we found out that:
- Users who only used one combination of a few navigation tools (e.g., zoom-in and zoom-out or scale choice list plus pan or recenter tool plus pan tool) needed much fewer clicks and overall time;
- Users who utilized four or more different tools needed more clicks and time to navigate to the right place.

This result is not surprising because of the system's response time on clicking and because each click produces a new map state that requires the user to realign himself or herself and to figure out the next steps.

As already mentioned, the task to digitize a parcel represented a considerable effort for most users. Users who had to start digitization over needed more time than other users.

In conclusion, users needing few tools and making few clicks needed less time than users who tried out different navigation tools and who made many clicks.

**Is there an identifiable connection between the user's performance and the user's satisfaction?**
Measuring the user's satisfaction is more difficult than measuring performance, for satisfaction is an individual opinion that can be divided into two statements:
- The user is satisfied with the functionality the system offers—the system enables the user to do the things he or she wants to do.
- The user is satisfied with how a feature or a tool works.

We did not explicitly ask whether the user was satisfied for the user's response might either correspond to either one or both of these statements. We therefore tried to approach the measurement of satisfaction with:
- The grade of difficulty the user had given to that task (ranging from 1 to 5) for difficulty must have an influence on the user's opinion of specific interface features and
- The comments the users had given during that task.

Comparing the grade of difficulty with the user's performance, we did not find any clear evidence for a direct connection between performance and the user's rating of the difficulty. In some cases, however, we did find a reason for the user's performance in the user's comments. Three users commented that RIV's map navigation is not functioning as in other systems the users had been using; in these cases, the users first had to figure out how RIV's map navigation works and therefore needed more time.

In the second questionnaire that was distributed after the hands-on evaluation, we used three statements (rating from 1 to 5) to indicate the user's confidence in the interaction with the system:
- “You always know where you are in the system.”
- “The workflow of operations is intuitive.”
- “It's always clear and comprehensible what is happening.”

In the analysis of the users' responses to these statements, we assumed that users who understand where they are, see and experience what they expected, and know what they are doing are more satisfied than users who do not. Considering these statements, we could see a tendency that this assumption was true: Users who needed less time, less clicks, and fewer tries (one or two tries) to digitize a parcel responded to the three statements with the highest grades (three or four users).

Given the data and the parameters that we had for measuring user satisfaction, we did not find any evidence for a connection between the user's satisfaction and the user's performance; however, we did find slight evidence that users who stated that they were more confident in the interaction with the system performed better.
Specific Interface Features Influence

Is there any evidence that some interface features cause a higher cognitive load?

To identify interface features that cause a higher cognitive load, we considered the following elements as indicators:

- The user's rating of the difficulty of a specific task;
- The user's comments on specific features; and
- The user's slower performance because of the features that the user had difficulties with.

At first, we analyzed the difficulty level the users had given to each task. The tasks with the highest difficulty level were: creating the first parcel, selecting two parcels (with the tool to select parcels), selecting different layers, and navigating to the Vully region.

Interface features that the users commented on were the navigation tools: to zoom in, to zoom out, and to move the map (pan). These tools were configured to work in the following manner:

- The user selects a tool and interacts with the map; if the user wants to change from zoom-in to zoom-out, the user has to select the tool by clicking on it—the user navigates the map by clicking on it with the selected tool;
- The user uses the zoom-in tool by drawing a rectangle on the region that the user wants to zoom in on;
- The user uses the pan tool by clicking on the map and moving the map—when the user stops clicking, the map is updated.

Some users commented that the zoom-in tool was difficult to understand. In fact, only five of 20 users used the zoom tool as intended (drawing a rectangle of the region to be zoomed in) and of the 15 users who did not draw a rectangle, ten accidentally drew a small rectangle (by clicking on the map a little bit longer) and zoomed in to the maximum level (1:100). The result of this problem was that:

- Users had to regain orientation on the map;
- Users had to use different methods to zoom out again;
- Users had either the impression that they did something wrong or that the system's zooming function is bad.

Moreover, ten users had a problem with the zoom-out tool (18 of 20 users tried to use it). All ten users clicked on the tool and expected the map to change (the idea was, as mentioned, to select the tool and then to interact with the map only). Thus, the users had to figure out a solution:

- Three users chose a different solution of zooming out (two the scale choice list, one the recenter tool);
- The other users discovered after a while that a click on the map was necessary in order to zoom out. However, two users each time they wanted to zoom out clicked first on the tool and then on the map.

The pan tool was used by only 12 users; two users commented that they did not understand how it was supposed to work and another user said that he would have preferred small arrows around the map in order to move it.

As a result, we can say that the manner in which the stan-
standard navigation tools are implemented in RIV can cause a high cognitive load.

In parallel to the problem with the zoom-in tool, the users had the same problems with the tool when selecting several parcels. The user could either use it to select one parcel by clicking on it or draw a rectangle to select several. As the task was to select several parcels, the user had to find a solution.

Only six out of 20 users knew or found out how to use this tool (by drawing a rectangle). The other 14 users were using either the menu “Parcel Groups,” where the user simply could choose the parcels from a list, or the tool to query parcel by selecting different criteria (both offer the possibility to save the selection of parcels).

The task to digitize a parcel was an interesting issue for the discussion of the cognitive load of specific interface features because half of the users had a small text that gave a hint on how to use the parcel digitizing tool; therefore, we analyzed these tasks for both groups of users (first ten users, last ten users) separately.

The first group (who did not have the hint) needed much more time to navigate and to digitize than did the second group. Only the digitizing part took almost twice as much time for the first group than for the second group. Surprisingly, when both groups were asked to digitize the second parcel, the first group digitized and navigated quicker than did the second group.

In conclusion, the feature to draw a rectangle on a map (either with the zoom-in tool or the select-object tool) does cause a higher cognitive load. In the case of a problem, the user had to find a different solution to solve a task that involved map navigation or the selection of objects. Moreover, the parcel digitizing tool did cause a high cognitive load for the user for the user had to discover its functionality during the task.

Were there differences in performance that were associated with features of RIV that are common with conventional GIS versus less conventional/interactive tools?

To define features that are typical for conventional GIS, we first analyze which interface features exist in both RIV and conventional GIS. As examples for conventional GIS, we refer to the GIS most commonly used at our laboratories: ArcGIS, MapInfo, and Manifold:

- A map that is built up by different layers;
- Navigation tools to navigate the map;
- Tools to create and to manipulate georeferenced data; and
- Tools to query this data.

Map and Layer Model. The map is the central part in all conventional GIS. It is composed of layers that are organized in a hierarchical manner. The user can display different layers in different modes and reorganize them. In all three conventional GIS we considered, layer management is done very differently (ArcGIS—a layer tree lets the user organize and display the different layers; Mapinfo—a toolbox, accessible through the main menu, displays the layer management; and Manifold—a map window where the layers’ vertical position symbolizes the layers’ hierarchical position and layers can be deactivated by clicking on the layer’s name (see Figure 5)).

In RIV, the ArcGIS layer management system was adopted (see Figures 5 and 6) with the extension that the user could choose between different layer categories.

Moreover, the display of some layers changes automatically from scale to scale (e.g., at a scale of 1:1,000 the user sees aerial images; at a scale of 1:25,000 the user sees a map that is optimized for that scale; and at a scale of 1:100,000 the user sees a different map).

Despite the fact that users had problems finding some layers because of the selection of the different layer categories, all users performed well while using this feature.

Navigation Tools. As mentioned previously, the following problems occurred for many users while they were using the navigation tools:

- Drawing a rectangle to zoom in and to select features and
- “Selecting” a tool that manipulates the map.

Both interaction methods are standard in all conventional GIS we considered.

Tools to Create and Manipulate Georeferenced Data. In conventional GIS, a huge variety of tools exists to create and manipulate georeferenced data, such as different digitizing modules, tools to create buffers, etc.

The digitizing tool that was implemented in RIV was conceived with a conventional GIS in mind: In all conventional systems, digitizing is always performed by clicking on the vertices of the object—a click on the next vertex adds a new segment of the polygon until the polygon is closed. In RIV, the user has to
click on the first vertex (after adding more vertices) to close the polygon.

As mentioned previously, many users had problems digitizing a parcel in RIV. Users made many errors and needed much time and effort to digitize a first parcel. We believe that this problem also is related to a conflict of interaction methods (in a Web context versus a GIS context) and that there was no possibility the user could know how the tool worked. Moreover, we discovered that some users hatched their parcels with the digitizing tool or just drew each line by using the mouse button clicked. We believe that this fact is related to the following issues:

Digitizing in a GIS context means creating vector data that is represented by points and lines. However, a parcel representation in terms of lines and points is not necessarily the representation a winegrower has in mind when thinking of his or her parcel.

The closest we can come to a digitizing task on a computer is probably to draw a parcel on paper. Drawing on paper is done by drawing a pen along a line. Many users probably considered the digitizing task as related to drawing on paper.

Unfortunately, we were not able to implement a better way to help the user digitize, so we decided to explain it by using a short text.

Tools to Query Georeferenced Data. In conventional GIS, a variety of different possibilities exists to query georeferenced data. The most common way to query georeferenced data is through the query language SQL that permits running all kinds of different scripts. Some GIS (such as MapInfo or ArcGIS) have toolboxes that let the user chose possible operators and data from scrollbars to form an SQL or SQL-like query string.

In RIV, we decided to implement a task with only one spatial operator (within) and one nonspatial operator (is equal to) for a menu called “Search by Criteria.” The user could chose between a variety of different spatial and nonspatial attributes that should be true. Moreover, we tried to form a natural sentence “Search all parcels for the following attributes” and then for each attribute a scrollbar.

The task to query all their parcels and to search for parcels with specific attributes or that were within specific regions worked very well for all users; we believe that the fact that we tried to form a natural sentence on the page helped the users to use this feature.

**USER EXPERIENCE AND TRAINING INFLUENCES**

Are there identifiable differences between users?
In our first questionnaire, we used four statements that we consider indicators of the user’s experience with computers and cartography:

- The user has taken courses in informatics (e.g., word processing, etc.).
- The user has a high-speed connection to the Internet.
- The user is a frequent user of paper maps.
- The user previously has used cartographic systems.

We assume that users who have taken courses in informatics know how to use a computer’s input devices (keyboard and mouse) and know how a computer reacts on this interaction. Furthermore, we presume that users who have high-speed Internet connections are more likely to spend more time on the Internet (and probably also are using applications that require a high bandwidth) than users who do not. We think that users who utilize paper maps frequently have an idea how the reality is depicted on such maps, what a map scale is, and how cartographic symbols are used.
Finally, we argue that the interaction with cartographic systems also has a significant impact on the use of RIV.

We found that out of 20 users:
- Seven users had answered yes to all four statements;
- Eight users to three statements;
- Four users to two statements; and
- One user to only one statement.

Is there any evidence to suggest that a user’s geospatial technology expertise has an influence on the user’s performance and on the way the user interacted with the interface?

We think that geospatial technology expertise is a combination of mainly two different elements: computer expertise and experience with geographical information.

Previously, we have detected measures that we judge relevant for both of these elements. Our assumption is that users who have answered yes to all four statements are likely to perform better than users who have answered no to at least two statements.

We used the following measures from the first task (which was the first time the users had to use RIV’s mapping system) as indicators for performance:
- The time to navigate to the parcel;
- The number of navigation clicks to navigate to the parcel;
- The time to digitize a parcel (considering the fact that the second group had an explanation of how to digitize); and
- The number of tries to digitize a parcel (considering the fact that the second group had an explanation of how to digitize).

We found the following evidence in our data:
- The user who performed worst in digitizing (from the first group) had answered yes to only two statements.

All but two users had used online mapping systems before this evaluation; many users had used two or three different systems. GéoPlaNet, the canton’s official mapping system, was the most known of those ten alternatives we had listed. Moreover, two users indicated that they had used some installable mapping systems before (Twixtel and ArcPad) and one user mentioned that he had used a GPS before.

All these systems are either way-finding systems (Mappy, Michelin, Map24); pure mapping systems (GéoPlaNet, Swissinfo); hybrid systems (Google Maps); systems with specific information such as railway stations (CFF) and infrastructure (Map Search) and a virtual globe (Google Earth). All systems have different navigation methods with different tools that are used to zoom in and zoom out or to pan.

Because we found that navigation tools in RIV are especially problematic for many users, we analyzed how map navigation works in these systems (see Figure 7). We analyzed if:
- The system reacts directly on clicks on the navigation tools.
- There is a scale choice list that permits zooming.
- The zoom-in tool supports a “rectangular zoom.”
- There are arrows around the map that the user can click on to move the map.

We found that four of the ten systems do support a “rectangular zoom”; however, all but one of these systems do support zooming through the scale choice list (one system’s scale choice list partly worked). We can further see that six systems are offering map navigation that does not involve clicking directly on the map—these systems support arrows for moving the map in each direction and a scale choice list.

We compared the manner each user interacted with the system and analyzed:
- If users who used the rectangular zoom in RIV were in

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<th>Rectangular Zoom</th>
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Figure 7. Different systems that users had employed before the evaluation
contact with systems who also support this feature;
• If users who had problems with that feature were in contact with systems that support other navigation methods;
• If users who tried to click on the zoom tools without afterwards clicking on the map were using systems that support that feature; and
• If users who frequently used the scale choice list were in contact with systems that support that feature.

We found the following evidence in our data:
• Four out of five users who used the rectangular zoom stated that they had been in contact with systems supporting this feature;
• Nine out of ten users who had problems with the rectangular zoom had used systems that support other possibilities to zoom than a rectangular zoom (the one user who had the problem had not used any cartographic systems before);
• Eight out of ten users who initially expected the system to react after clicking on the zoom tool had used systems before that support a direct click;
• Seven out of nine users who used the scale choice list had been in contact with systems supporting this feature (the two other users had not been in contact with any cartographic system before).

We found out that there seems to be a connection between the user's background, in terms of expertise in computers in general and experience with geographical information and the way they interacted with RIV. Moreover, there is a likely connection between the geospatial systems the users had used before and the methods the users performed in this evaluation.

DISCUSSION

In our evaluation, we found some evidence that supports our hypotheses. We focused mainly on the first tasks in which the users interacted directly with the map.

We could see that the 20 users in our evaluation did have different methods to interact with the system and that some methods resulted in different performances.

The problems that occurred were not only linked to one cause but to many specific reasons. We found evidence that users are highly influenced by their previous experience with geographical information and computer systems. Users who did not find the interaction method they were used to were forced to find different ways to interact with the system and thus performed worse than users who found the interaction methods they were used to. This is especially the case using the navigation tools.

The problems that occurred with these navigation tools were mainly because of two reasons:
• RIV is a system that is used in a Web context. In a Web context, a click on almost all standard elements (buttons, checkboxes, radio buttons, links, menus, etc.) has a direct effect on the display's state (e.g., one click on a hyperlink makes the system navigate to the next page). Using the conventional GIS interaction method of selecting a tool and then interacting with the map is a rupture in the Web context. Also drawing a rectangle is a rupture of this context for all standard objects that are clickable in a Web context usually are points—the user is used to moving the mouse to one feature (button, link, etc.) and then clicking on that feature. Drawing a rectangle implies holding the mouse button for a longer time and moving the mouse while clicking.
• In RIV, there was no possibility the user could have known that the navigation tool could have been used in this manner; neither the icon of the zoom-in tool suggested it, nor did a text indicate it.

Regarding our hypothesis that there is a connection between performance and satisfaction, we only found very poor evidence with the measures we had taken and methods we had chosen.

As previously mentioned, satisfaction is an individual opinion; possibly, not only the user's performance but also the user's experience can have a positive or negative influence on the user's performance and satisfaction. For instance:
• Users who were less used to computer systems and geographical information and needed more time may have been surprised to see the possibilities of such systems and thus were satisfied with the systems.
• Users who were more used to these elements and performed better could have expected more or different functionality and thus were less satisfied.
• An interesting point was the task to create the first and the second parcel. Although the second group was provided a small explanation in the system indicating how to digitize a parcel, the performance for the second task was slightly lower than the first group’s performance when doing the same task. We believe that this fact could have a relation to Bloom's Taxonomy of Educational Objectives, which says that there are different levels in the cognitive domain: knowledge (low level), comprehension, application, analysis, synthesis, and evaluation (high level):
  • The first group was forced to understand and to learn how to digitize a parcel by trying out. The cognitive level thus was higher; but once the users understood and tested the task several times, it was easier to do the same task again.
  • The second group “simply” followed instructions while they were doing the task and succeeded after one or two tries. However, when creating the second parcel, the second group only had a lower-level cognitive picture of the task and less practice in performing this task and thus performed slightly lower.
CONCLUSION AND FUTURE RESEARCH

We found that the interaction of a real-world user with a specific WebGIS complex compared to the interaction with a “normal” homepage with hyperlinks and content. It requires other cognitive strategies such as navigation in a virtual space using specialized tools and the interpretation of specific maps.

Despite the fact that we only had 20 persons who evaluated the interface, we could see that users performed very differently. These differences were caused by a set of factors that can be considered from the point of view of:

• The interaction between the user and the system (user strategies, performance, and satisfaction);
• The system (interface features);
• The user (experience and training).

We established hypotheses depending on these categories and we tried to accept or reject these hypotheses by answering the research questions.

Although we could not entirely accept or reject these hypotheses because of the limited number of users, we found evidence about the links between these categories. Moreover, we were able to find some tendencies and trends and to detect interface features that did cause problems for many users.

The methodology we have developed to answer the research questions is capable of delivering evidence about the level of connection between these factors. We believe that this methodology can be used for the evaluation of most WebGIS, even if they are based on different technologies.

In the future, we will refine our evaluation methodology with further tests involving different systems, users, and evaluation tasks.

Within our research program, the long-term goal is to analyze the importance of these factors; for instance:

• Which user experience and training factors are more important?
• Which factors do have an influence on the user’s satisfaction?

Based on this research, we want to establish guidelines for developers and system designers on how to build specific systems for particular groups of users (e.g., it is better to develop a system with the zoom-box feature for users with much experience in the field of geoinformation for they would expect the system to have it, while it is more reasonable to develop a system without this feature for less experienced users).

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Web-PPGIS Usability and Public Engagement: A Case Study in Canmore, Alberta, Canada

Yunliang Meng and Jacek Malczewski

Abstract: This paper quantitatively evaluates the usability of a Web-based public participatory GIS (Web-PPGIS) and the degree of public engagement in the context of a real-world spatial planning application. The public participatory decision-making process utilizes ArgooMap to support local residents in an online procedure for determining the “best” location for a new parking facility in Canmore, Alberta, Canada. USAProxy is employed to automatically collect the data sets on the system usability and the degree of public engagement. This research shows that the degree of public engagement depends significantly on the system usability measured in terms of the system efficiency and effectiveness and the participants’ satisfaction with using the system. These findings provide an important implication for designing Web-PPGIS.

INTRODUCTION

Over the past decade or so, public engagement has increasingly been an important theme in the urban planning process (Talen 1999, Kingston et al. 2000, Keßler 2004, Kingston 2007). This assertion is based on the premise that public engagement in the process can lead to a more sustainable, legitimate, democratic, and effective plan. Public meeting is one of the most popular methods of public participation. The method requires that the meetings are held in a certain place during a fixed period of time. This limits the number of people who can be involved in a decision-making/planning process. Therefore, there is a need for developing tools that can enable and support new ways to involve the citizens in the decision-making process (Krek 2005). In the past, various tools (a three-dimensional cardboard scale model, poster, kiosk, etc.) have been used to facilitate public participation (Rambaldi and Callosa 2000, Berner 2001). Since the late 1990s, the high-powered computer, the low-cost desktop GIS, and decision support software have been used for supporting community collaboration and public participation in urban and community planning processes (Craig and Elwood 1998, Klosserman 1999, Talen 1999). This has been developed into a broad area of research, generally referred to as public participatory GIS (PPGIS). However, traditional GIS has been criticized as an elite technology (Pickles 1995), which is operated mainly by a small group of scholars, GIS technocrats, and planners because of high operation costs, complex design, and great learning barriers. A little progress has been made to encourage the general public to join in community-based GIS projects (Chua and Wong 2002).

In recent years, the appearance of the Internet and improved WWW technologies provide opportunities for PPGIS researchers. This has speeded up the incorporation of PPGIS into the WWW technologies (Kingston et al. 2000, Keßler 2004, Simão et al. 2009). This type of system often is referred to as Web-based PPGIS (Web-PPGIS). Web-PPGIS overcomes many problems caused by the traditional GIS and conventional public participation methods (Kingston et al. 2000, Chua and Wong 2002, Keßler 2004). For example, people can join the public participation process at any time and at any place that has a computer and Internet service. The complexity of GIS and spatial analysis is hidden from the user. A Web-PPGIS enables people to express their views by posting comments in a relatively anonymous and nonconfrontational manner. It also supports two-way to multi-way flows of information.

Most Web-PPGIS research and projects have focused on making Web-PPGIS available and accessible to the general public to stimulate more informed participation and decision making (Sieber 2006, Kingston 2007). At the same time, the rapid technical progress in the area of developing Web-PPGIS has raised some questions regarding the evaluation of Web-PPGIS technology. One concern is related to the usability of Web-PPGIS. When an increasing number of laypeople obtain access to a Web-PPGIS, it is important to raise the issue of how usable the system is for a wide range of potential users. Web-PPGIS practitioners need not only upload a Web-PPGIS to a Web site, but also must design it in an effective, efficient, and satisfying way for users to perform specific tasks (ISO 1998). If the system usability is unsatisfactory, this could cause issues such as wasting users’ time, making them worry and frustrated, and eventually discouraging their engagement in the public participatory process. This leads to the concept of degree of public engagement that, in this study, is referred to as the degree of public participants’ interactions with the Web site holding a Web-PPGIS and other participants in the online public participatory decision-making process against a set of clearly defined goals.

An important objective of Web-PPGIS projects is to use the technology to engage grassroots public members in the decision-making process. Thus, we suggest that empirical studies are needed to (1) evaluate the usability of a Web-PPGIS and the degree of public engagement quantitatively and (2) explore the
Web-PPGIS usability as the determinant of the degree of public engagement. These two research objectives will be investigated by using a Web-PPGIS: Argoomap (Rinner 2001, Keßler 2004) for tackling a multicriteria site selection problem, which involves public participants determining the “best” location for a new parking facility in downtown Canmore, Alberta, Canada.

The paper is organized as follows. The following section provides a brief review of the system usability evaluation and public engagement, including the levels and degree of public engagement. Then the paper demonstrates how to collect the system usability and the degree of public engagement metrics for different users in a real-world public participatory planning situation. The next section provides the results and analysis on the relationships between the system usability and the degree of public engagement. Finally, discussion and conclusions are presented.

### Usability Evaluation and Public Engagement

Usability evaluation refers to the process of systematically collecting data on how people use the system for a particular task in a particular environment (Preece et al. 2002). Two main types of methods are used to evaluate usability (Banati et al. 2006). First, the inspection methods (e.g., the heuristic evaluation, cognitive walk-through, and walk-through inspection) mainly involve system developers or experts to do the test following a set of schemes. Second, the user testing methods involve a set of procedures for collecting data when users interact with the system to perform prespecified tasks. Then the system usability can be quantified in terms of users’ performance and satisfaction during the interaction with the system (Butler 1996). No general rule exists for how usability measures should be chosen or aggregated (ISO 1998). However, it is suggested that at least one measure of effectiveness, efficiency, and satisfaction be provided (ISO 1998). In addition, how to choose the measures and decide the details of each measure depends on “the objectives of parties involved in the measurement” (ISO 1998, p. 10).

There is some usability research performed in the context of Web-PPGIS. Haklay and Tobón (2003) discuss the association between human-computer interaction (HCI) and usability evaluation. They argue that software characteristics such as ease of use and user friendliness are more elusive than one may expect, so only appropriate testing can verify whether the system design is successful in meeting users’ needs. Sidlar and Rinner (2007) provide a case study focusing on different aspects of the usability of a Web-PPGIS: Argumentation Map (Rinner 2001, Keßler 2004). Although considerable progress has been made in advancing research about the system usability (Haklay and Tobón 2003, Sidlar and Rinner 2007, Haklay and Zafiri 2008, Ingensand and Golay 2010), there are no studies on measuring various aspects of usability systematically and quantitatively.

The phrase public engagement in the urban planning context refers to a process of bringing together citizens, community non-profit organizations, businesses, and government to solve planning problems that affect everybody’s life (Rabinovitch 2004). It often is used haphazardly in PPGIS research and confused with the notion of public participation. Public engagement suggests a degree of personal choice, commitment, and willingness (Rabinovitch 2004). It also implies an interweaving of responsibility, action, and a degree of control. PPGIS practitioners tend to use the ladders of public participation as the conceptual framework to guide public participation (Arnstein 1969, Weidemann and Femers 1993, IAP2 2004). In PPGIS literature, the term public engagement often is used interchangeably with the notion of public participation when it refers to high levels of public participation activities (see Table 1).

<table>
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<tr>
<td>Citizen Power</td>
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<td>Empower</td>
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<td>- Citizen control</td>
<td>- Public participation in assessing risks and recommending solutions</td>
<td>- Implement what the public decides</td>
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<tr>
<td>- Delegated power</td>
<td>- Public participation in defining interests and actors and determining agenda</td>
<td>- Collaborate</td>
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<tr>
<td>- Partnership</td>
<td>- Public right to object</td>
<td>- To identified preferred solution with the public</td>
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<td>Tokenism</td>
<td>- Informing public</td>
<td>- Involve</td>
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<td>- Facilitation</td>
<td>- Informing the public</td>
<td>- To work directly with the public</td>
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<tr>
<td>- Consultation</td>
<td>- Public right to know</td>
<td>- Consult</td>
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<td>- Informing</td>
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<td>- To obtain public feedback</td>
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<td>Nonparticipation</td>
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<tr>
<td>- Therapy</td>
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<td>- To keep people informed</td>
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<td>- Manipulation</td>
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Table 1. Ladders of public participation
by providing access to the relevant tools, data, and information to enable more informed engagement and decision making. However, the assumption is questionable.

After adopting the new technologies to facilitate public participation, the feedback from local community members sometimes is quite frustrating. Lee (2000) demonstrates that about 34 percent of all users visit the Web site holding GIS on a monthly or occasional basis. Hopkins et al. (2004) find that some participants often just give up in the middle of the participation process because of great learning barriers and complicated interfaces. Sidlar and Rinner (2007) and Ingensand and Golay (2010) report that the project ends up having a few number of participants. Although the general public has the opportunity to contribute and exert its influence on the project, it seems that many people are reluctant to become engaged. This is an issue long ignored by Web-PPGIS professionals. This evidence suggests that providing an improved access to the systems and relevant data no longer is sufficient to enhance the degree of public engagement in the participatory decision-making process.

May (2007) introduces a model called Triangle of Engagement that can be used to explain the relationships among the level of public engagement, the degree of public engagement, and the prevalence (the number of participants engaged) (see Figure 1). In the model, the level of public engagement increases from the base to the apex. Each level of public engagement corresponds to a different degree of public engagement that costs the participant varying amounts of time and energy (May 2007). The higher up the triangle, the higher the degree of public engagement and the less the prevalence. However, the May (2007) model descriptively discloses the relationships among the prevalence, level, and degree of public engagement rather than quantitatively. It does not demonstrate how to measure the degree of public engagement quantitatively. It falls short of explaining why some participants could commit to a higher degree of engagement than others while they have joined the same level of public participation.

**CASE STUDY**

**Study Area**

Canmore, Alberta, Canada, is located in the Canadian Rocky Mountains (Kananaskis Country), approximately 20 kilometers east of Banff and 100 kilometers west of Calgary (see http://www.canmore.ca). The town is an administration and business center for residents and employees of the Banff National Park, Kananaskis Country, and the Bow Valley. It has a population of approximately 16,000. Canmore is a transitional town experiencing changes because of tourism expansion. As a result of growing population pressures and changes in the nature and intensity of economic activities, issues of land-use planning have become increasingly important (Town of Canmore 2007).

**Evaluating Sites for Building a Parking Facility in Canmore, Alberta, Canada**

Two groups of people (local residents and tourists) contribute to the demand for parking facilities in downtown Canmore. The tourists can be further categorized into the day-visit tourists and stay tourists depending on whether they stay overnight in the town. The day-visit tourists usually stay in Canmore for just few hours. They get off Highway 1 by Benchlands Trail Overpass,
drive to downtown Canmore for a meal, gas, or other short-time activities, and then head to other places without staying overnight. The stay tourists spend at least one night in Canmore. The number of hotel room units is used to quantify the demand from the stay tourists. In Canmore, the private vehicles are the dominant transportation mode for local residents. However, the local government does not collect vehicle ownership statistics. Therefore, the 2006 Canmore population data are used as an approximate measure for the demand for parking from the local residents. The Local Delivery Units (LDUs) (the smallest postal delivery zones, see Figure 2) are employed for describing the spatial distribution of population and stay tourists. The centroids of each LDU and location of Benchlands Trail Overpass are used as demand points. There are 410 LDUs in Canmore.

The Planning Department of Canmore has preselected four candidate sites for a new parking facility in downtown Canmore (see Figure 2). However, the department welcomes any suggestions or recommendations from local residents regarding potential locations for constructing the parking facility. Nevertheless, only the four candidate sites will be evaluated and ranked quantitatively.

A set of criteria including (1) weighted average distance to local residents, (2) weighted maximum distance to local residents, (3) weighted average distance to stay tourists, (4) weighted maximum distance to stay tourists, (5) distance to Benchlands Trail Overpass, (6) distance to Main Street, (7) the number of people living within 100 meters of a candidate site, (8) the size of a candidate site, and (9) the cost of land acquisition are employed for evaluating the suitability of a candidate site. Except for the size of a candidate site, all evaluation criteria are to be minimized.

**ArgooMap**

ArgooMap is based on the concept of an Argumentation Map that provides a foundation for Web-PPGIS tools design and development (Keßler 2004, Rinner et al. 2008, Boroushaki and Malczewski 2010). In the Argumentation Map model, argumentation elements and geographic reference objects are regarded as independent entities (Rinner 2006). The relationships between a user-initiated discussion and the discussion-related place on a map are specified. In addition, the model includes user-defined graphic reference objects and supports the many-to-many relationship between any kinds of objects.

The design of ArgooMap (second version of Argumentation Map) is an AJAX-based implementation with Google Map interface. ArgooMap was customized by Boroushaki and Malczewski (2010). The customized ArgooMap consists of three main sections: (1) registration and log in, (2) main map, and (3) questionnaire about the user’s characteristics (see http://www.ParticipatoryGIS.com). The registration and log-in section is composed of four different pages: “Log In,” “User Registration,” “Terms and Conditions,” and “About ParticipatoryGIS.” The main map section of the system contains two Web pages: “Tutorial” and “Main Decision Map.” The Tutorial contains two parts. The first part describes the goal and objectives of the parking site selection problem, provides a detailed description of the address of each candidate site and photos of the sites, and explains the evaluation criteria. The second part provides screen shots and instructions on how to join the online public participatory decision-making process. The Main Decision Map contains a multicriteria decision analysis (MCDA) module. The user can give his or her preference regarding the importance of each criterion by choosing one of the following terms: none, very low, low, medium, high, and very high (Chen and Hwang 1992). In addition, the participants have to select a linguistic quantifier (Boroushaki and Malczewski 2010) to indicate how the attribute data and their preferences will be aggregated to provide the final scores and rankings of the alternative sites. In the Main Decision Map element, the users can use the “group decision” function to explore the decision outcome based on group preferences. The function generates rankings and suitability scores for the alternative sites based on the fuzzy majority procedure (Pasi and Yager 2006). In the Main Decision Map, the users can explore the area using the zoom-in/zoom-out function or shift the background map to a satellite image or a map-satellite image hybrid module. The attributes of each alternative can be retrieved by clicking one of the four alternatives. The users can read existing comments and initiate a discussion or reply to an existing thread by turning on the “discussion board.”

**Recording Public Participants’ Move**

To evaluate the usability of ArgooMap and measure the degree of public engagement in the online public participatory decision-making process, public participants’ every move on the Web site was recorded using UaProxy (Atterer et al. 2007). UaProxy uses an HTTP proxy approach that works with the current server and browser setups. It employs JavaScript technology that stands behind the client-side monitoring, so the activities of users on the Web site are not affected (Atterer et al. 2007). By using the software, it is possible to collect highly detailed and useful log data about the actual usage of the Web site and the ArgooMap system. Actions such as moving the mouse pointer, scrolling a page, or filling out a form in a specific order, etc., were automatically recorded into a log file stored on the server where UaProxy and ArgooMap were installed. In addition, the events, such as opening a Web site, logging in the system, and clicking a button, were directly written into the log file. This data recorded in the log file are useful for evaluating the usability and measuring the degree of public engagement.

An example of the log data generated by UaProxy during the public participatory decision-making process is shown in Figure 3. The log output displays events such as mouse move (pointer position changed), mouse over (the pointer was moved over a DIV HTML element or something similar), focus (the cursor was moved into an input field), etc. Users’ IPs, the time of the events, and the coordinates of the mouse pointer are recorded along with the events.
Generating Usability and Degree of Public Engagement Metrics

The design of ArgooMap is based on the “walk up and use” principle. In other words, the system is supposed to be used by first-time users who do not need any training before being able to effectively use the system. Therefore, the metrics employed for evaluating the usability of ArgooMap are the “walk up and use” measures suggested by ISO (1998) as well as measures proposed in previous research/projects (Nielsen 1993, Haklay and Tobón 2003, Sidlar and Rinner 2007). The measures of usability include effectiveness, efficiency, and satisfaction.

Effectiveness refers to the “accuracy and completeness with which users can achieve their goals” (ISO 1998, p. 19). In this study, the effectiveness is measured by the number of major tasks completed successfully on the first attempt (ISO 1998). The major tasks involve using three groups of functions available in ArgooMap system: mapping, deliberation/argumentation, and MCDA. The first major task is to use mapping functions to explore the study area. The functions include zooming (zoom-in and zoom-out) and background view change (map view, satellite image view, and map-satellite hybrid view). The second major task is to use the deliberation/argumentation functions to communicate with other participants regarding the existing four candidate sites, other possible candidate sites, or other concerns related to the parking site selection project. The functions are reading comments from previous users and initiating a new georeferenced discussion or replying to an existing georeferenced discussion. The third major task is to use MCDA functions to resolve the site selection problem. The functions used in the third task include site attribute inquiry, group decision-making outcomes inquiry, and identification of the best site using an ordered weighted averaging (OWA) module (Yager 1996, Boroushaki and Malczewski 2010).

Satisfaction is defined as “freedom from discomfort, and their attitudes towards the use of the system” (ISO 1998, p. 19). Satisfaction is a response of the users when interacting with the product. In the questionnaire section, the users were asked to rate their overall experience with ArgooMap on a six-point scale ranging from zero to five (with zero the lowest score and five the highest score).

Efficiency refers to the system’s ability to fulfill the level of effectiveness while taking a certain amount of resources (ISO 1998, Sidler and Rinner 2007). It is measured by the time needed to perform a prespecified task on the first attempt. As mentioned, users were asked to perform three major tasks using a number of functions. For mapping functions, the time spent on zooming or background view change depends on the objects (size, color, contrast, etc.) that they are exploring, so the time used to zoom or change the background view on the first attempt cannot be used to measure efficiency. In terms of deliberation/argumentation functions, the length of comments posted by the users and their typing speed are quite different. The time used to read comments posted by other users depends on available comments and the length of comments. In addition, only a limited number of users posted or read comments. Thus, the time used to post or read a comment on the first attempt cannot be used to measure efficiency. Every user performed MCDA and the time spent on identifying the best site using the MCDA module is comparable. Therefore, the time used to identify the best site on the first attempt using the MCDA module is chosen to measure the system efficiency in this study.

Peterson (2008, p. 5) describes user engagement in the context of the Web analytic as “an estimate of the degree and depth of visitor interaction on the site against a clearly defined set of goals.” In this study, there are two main goals: to promote the participants’ interaction with the Web site and to encourage the participants to interact with each other from the beginning to the end of the online public participatory decision-making process. They are encouraged to remain on the Web site, visit the Web site frequently, if possible,

Figure 3. A sample of the log output produced by UsaProxy
view every page, and join the discussion by posting new comments and reading existing comments. Accordingly, the degree of public engagement is measured by the following metrics: (1) the total time of stay on the Web site, (2) the number of total visits, (3) the number of page views, (4) the number of comments posted, and (5) the number of times to read comments.

**Results and Analysis**

The ArgooMap system and relevant data were uploaded to www.participatorygis.com for use from October 1, 2008, to December 30, 2008. Canmore residents were invited to identify their concerns, ideas, suggestions, or preferences for the candidate sites and evaluation criteria for locating a new parking facility in the downtown area. The ArgooMap Web site and the parking site selection project were advertised in the local community newspaper—Rocky Mountain Outlook. The advertisement also was displayed on the Web site of the Department of Local Economic Development and the Department of Planning and Engineering. Fifty-eight participants joined the online public participatory decision-making process.

**DESCRIPTIVE ANALYSIS**

**The Usability Metrics.**

The descriptive statistics for the usability metrics are summarized in Table 2. For the number of major tasks completed successfully on the first attempt, the data shows that most of the participants performed at least two major tasks. The average time to perform a task on the first attempt is 131 seconds, but the standard deviation of 74 seconds indicates that the participants spent a wide range of time finishing the task. The average subjective satisfaction level of using the ArgooMap is fairly high (slightly greater than three).

**The Public Engagement Metrics.**

Descriptive statistics of the degree of public engagement metrics (the total time of stay on the Web site, the total number of visits, the number of page views, the number of comments posted, and the number of times to read comments) are presented in Table 3. The total time spent on the Web site varies from 325 seconds (or about five minutes) to about 80 minutes, with an average of 18 minutes. The number of visits ranges from 1 to 3, and 62 percent of the participants visited the Web site once. The number of page views varies from 5 to 12, with the mean value of 7. In terms of the number of comments posted, 69 percent of the participants did not post a single comment. When it comes to the number of times the users read comments, more than half of the participants did not read comments and suggestions from others.

**The Relationships between Usability and the Degree of Public Engagement**

A summary of Spearman's correlation coefficients ρ (Spearman 1904) for the usability metrics and the degree of public engagement metrics is shown in Table 4. The correlation results provide...
detailed relationships among system usability metrics and the degree of public engagement measures. It demonstrates that different aspects of system usability have very diverse effects on various aspects of the degree of public engagement.

A longer time of stay on the Web site could maintain user interest in the site (Bucklin and Sismeiro 2003) and give users more time to consider and make a decision. As shown in Table 4, the total time of stay on the Web site has a significant relationship with effectiveness ($p = 0.377, p < 0.01$). However, the measure has statistically insignificant relationships with the efficiency and satisfaction metrics. These results are inconsistent with the findings of Langerak et al. (2003). In their research, satisfaction with the Web site (used to facilitate member-member and member-organizer interactions in their study) has positive effects on the member participation, which is quantified by visit frequency and duration. The correlation results show that the system effectiveness is a main determinant for users’ visit duration on the Web site holding ArgoonMap. The higher the system effectiveness that users obtained from interacting with the Web site, the longer they would stay on the Web site. This finding partly supports research conclusions by Danaher et al. (2006). They argue that Web site usability is one factor that has been shown to be correlated to Web site likability and the length and the depth of the visit.

The total number of visits is significantly correlated with two usability metrics: satisfaction ($p = 0.312, p < 0.05$) and efficiency ($p = -0.365, p < 0.01$), but it is insignificantly correlated with the system effectiveness (see Table 4). The correlation results suggest users’ satisfaction and system efficiency can be two major factors that determine the participants’ total number of visits. These findings are consistent with previous Web site usability research (McKinney et al. 2002, Langerak et al. 2003, Pearson et al. 2007). These studies suggest that the higher the level of users’ satisfaction with browsing the Web site, the larger the number of return visits. In the context of WebGIS usability, Lee (2000) suggests that the Web site usability has a direct effect on the likelihood of visiting the Web site. Nielsen (2003) argues that if the customer finds the site too difficult to use, there will be no return visits. Brandtzæg and Heim (2008) point out that low usability of online community Web sites is one of the main reasons why users decrease their participation frequency over time until they completely cease visiting the sites. The research findings at least partly support those conclusions by demonstrating that the system efficiency and users’ satisfaction have a significant influence on the number of total visits.

The number of page views is a term that often is used in Web-based marketing and advertising for predicting revenue. This measure is used here because the online public participatory decision-making process is completely Web-based so that the users are expected to go through all the pages to obtain the relevant information for resolving the parking site selection problem. As shown in Table 4, the number of page views is significantly correlated with the system efficiency measure ($p = -0.296, p < 0.05$). However, the system effectiveness and users’ satisfaction have no significant relationships with the number of page views. The correlation between the number of page views and the system efficiency indicates that the system efficiency is a major source influencing the number of page views. The higher the system efficiency (less time spent on performing the task on first attempt), the greater the number of pages the participants would view. Nielsen (1998) notes that because of its growing attention on Web site usability, Yahoo.com has experienced a 28 percent average increase in page views each year and an increase of 15 percent per year in earnings per page view. Farrell-Vinay (2008, p. 300) points out that “the website page views increase when the usability has been improved.” Thurow and Musica (2009, p. 95) suggest that “the page views increase after improving the usability of the website” in the context of Web searching. This study partly supports the previous research conclusions by showing one aspect of usability (the system efficiency) has a significant relationship with the number of page views.

Different ideas, suggestions, and discussions regarding the parking site selection problem are vital to the success of the project. This is because the participants may have the knowledge that planners don’t have; the participants can exchange their views to get fresh thoughts, understand each other’s point of view, and compromise. Therefore, both reading existing comments and posting new comments (initiating a new thread or replying to an existing topic) have been encouraged. As shown in Table 4, statistically significant correlations have been found between the number of comments posted and the system effectiveness ($p = 0.489, p < 0.01$) and the system efficiency ($p = -0.342, p < 0.01$). The number of times to read comments also is highly correlated with the system effectiveness ($p = 0.731, p < 0.01$) and the system efficiency ($p = -0.413, p < 0.01$). The correlation coefficients indicate that the system effectiveness and efficiency can be considered as two major sources having an impact on the degree that the participants interact with each other. The higher the system effectiveness and efficiency obtained by the participants, the greater the number of comments they would read and post. However, the number of comments posted and the number of times to read comments are insignificantly correlated with users’ satisfaction. Kim (2000) and Preece (2000) have independently presented a set of design principles and strategies for building social interaction Web sites that focus on users and their interactions. Their strategies overlap with each other on the design principle: the Web design for usability. Specifically, the principle focuses on improving usability so that users can interact and perform tasks easily and effectively. Although the principle is advanced in the area of Web designing for social interaction, it also is applicable in the area of Web-PPGIS where user interaction is a vital element for a successful application. The results of correlation analysis emphasize the importance of the principle by showing that two aspects of system usability (effectiveness and efficiency) significantly affect user interactions.
DISCUSSION AND CONCLUSIONS

Considerable advances have been made in the development of Web-PPGIS applications over the past decade or so. However, there are still many issues surrounding the system's usability. This paper has focused on examining the system usability as a determinant of the degree of public engagement. The relationships between the three aspects of the system usability (effectiveness, efficiency, and satisfaction) and the five metrics that quantify the degree of public engagement have been examined individually. At least one aspect of the system usability has a significant effect on each of the five degrees of public engagement measures.

The results of this research show that the system effectiveness has a strong influence on the users' duration on the Web site and interactions with each other. This suggests that Web-PPGIS designers should focus on improving the system features, such as navigating the Web site, locating desired documents, and enhancing content; design functions that work with standard Web browsers; and choose the right resolutions to attract users to stay longer on the Web site and interact more with others. The study has shown that the system efficiency has a significant impact on users' number of visits, number of page views, and interactions with others. These findings indicate that Web-PPGIS designers should advance and highlight certain features, such as using fewer buttons and clicks to get to the destination page, speeding up page loads, reducing steps in the process, and reducing the amount of information to be filled out so users visit the Web sites more frequently, view more pages, and interact more often with other participants. The level of satisfaction is significantly correlated with the number of visits. This finding indicates that Web-PPGIS designers should modify and enhance some features—such as making the task more obvious and intuitive so it is more easily completed by users—to attract users to the Web site more often.

The Web-PPGIS infrastructures (the Internet, discussion forum, GIS, decision support tools, etc.) alone are insufficient to retain and promote the degree of public engagement. The correlations between the system usability and the degree of public engagement show that an effort in improving Web-PPGIS usability is justified if a goal of the system applications is to enhance the degree of public engagement. The correlations also indicate that Web-PPGIS employed to ensure public participation in the project can itself become an obstacle for certain participants to effectively engage in the decision-making process. Notwithstanding all the advantages brought by using Web-PPGIS, the system can be used as a complementary tool rather than a replacement for the traditional public participation methods (such as public meetings, poster demonstrations, etc.). Some participants have great difficulties using this type of system for participatory planning. As a result, those participants may not be convinced that Web-PPGIS tools are “better” than the conventional methods and this can lead to a further division with respect to public participation using Web-PPGIS in the future. Therefore, we suggest that usability testing approaches (user-testing methods) should be integrated into the system design process so that Web-PPGIS designers can detect the usability problems and make changes to the system prior to the public participatory planning process.

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