Exploring Normative Scenarios of Land Use Development Decisions with an Agent-Based Simulation Laboratory

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Abstract Suburbia and exurbia have an undeniable appeal to many urban dwellers. At the same time, they are characterized by an ineffective and fragmented residential patchwork of developed and undeveloped tracts. This research addresses a question of whether other arrangements of land, ameliorating the negative effects of current growth in the suburban fringe, are feasible from the perspectives of planning agencies and property developers. In order to answer this research question, the study employs two loosely coupled land use models: multiobjective land allocation (MOLA) and an exploratory agent-based modeling (ABM) of residential development. The aligned modeling methodology has a number of advantages. Firstly, it combines top-down and bottom-up modeling. Such an approach is an attempt to represent society from two standpoints: institutions on one side (like zoning regulations of local planning agencies) and individual agents on the other (like developers). Secondly, the framework combines both static form (MOLA) and dynamic process (ABM). The MOLA model is equipped with mechanisms that encourage both compact and alternative residential land use arrangements. The outcomes of this model are used as zoning regulations in the ABM to examine the impact of regional-scale top-down urban growth plans on agent disutility which reflects the competitiveness of the local property market. Selected MOLA plans are further relaxed using different distance buffers. The findings point to a complex disutility-fragmentation relationship. Under the simulated planning situation, a potentially acceptable solution for planners and developers involves a relatively high compactness of development, which could satisfy agents' overall disutility.

1. Introduction

Suburbia and exurbia have an undeniable appeal to many urban dwellers. From the geographic perspective, they are characterized by a low-density and fragmented residential patchwork of developed and undeveloped tracts. Such buildup arrangements have been stimulated by cheap land, large-lot zoning, massive highway constructions, and increasing use of automobile. Together, they have led to an outward exodus from cities and resulted in a major loss of agricultural land and wilderness. Studies related to sustainable development suggest that inefficient resource use and high traffic congestion are more due to the pattern of growth than the amount of growth itself (Barton 1990, Randolph 2004). Therefore, there is a need to increase land use efficiency by designing, exploring, and evaluating alternative landscape arrangements. The primary problem involves the multiobjective and conflict-laden nature of sustainable growth management, where the near-optimal land use options are complex to determine and difficult to achieve. Therefore, the first step of this research is to generate a number of compromise disparate spatial solutions using a multiobjective land use allocation model (MOLA). The model directs the growth to economically viable and accessible sites that are environmentally appealing yet, at the same time, distant from ecologically sensitive areas. Moreover, the proposed MOLA promotes infill development.

Whether such sustainable patterns are possible at all in practice, given the inconsistency of human spatial decision-making, is another major research question. Problems of human ignorance, risk perception, or conjecture can result in far from optimal individual spatial decisions (Tversky and Kahneman 1981). In response to these problems, this research builds a spatial agent-based model (ABM) of residential developers to test the achievability of a compact growth management scenario in a simple artificial society. Since developers are the primary decision makers in the process of land use change, their attitudes towards risk may be the major driver influencing the resultant land arrangements (Trevillion 2002). Developer risk attitudes involve investment decision behaviors under the presence of uncertain, and hence, risky economic conditions and are modeled in this paper as risk attitude functions representing the risk prone, averse, and neutral behaviors (Ligmann-Zielinska 2009).

While traditional validation approaches, which compare the simulated and observed data, are useful when dealing with past events and processes, it remains unclear what reference data should be used for planning into the future. This paper offers one way to solve this problem by using the concept of model aligning (Axtell et al. 1996, Brown et al. 2004, Hales et al. 2003) that incorporates the results of MOLA, representing an idealized benchmark of municipalities that want to maximize growth efficiency, into an ABM that emulates the process of individual decision making aimed at maximizing the return on development investment.

The presented modeling framework consists of a morphological land use optimization and a dynamic spatial agent-based simulation. The MOLA model is a generative component addressing the first research objective that concerns optimizing an urban growth development pattern satisfying the criteria of compact and contiguous development growth. Consequently, the MOLA model is equipped with generative mechanisms that encourage diverse compact land alternatives to provide alternative visions for the future. The second stage of the modeling focuses on analyzing the impact of MOLA blueprints on the disutility of developer agents, which is caused by the lost development opportunities. MOLA outcomes epitomize exclusionary zoning plans (also called Urban Growth Areas – UGAs), which are superimposed on the developable land layer used as the input for ABM. The foremost goal of this research is to analyze whether agent development preferences and risk perception can be reconciled with normative patterns of growth so that the overall agent dissatisfaction, due to the loss of developable locations, is minimized while the compactness of development is maximized. Optimizing the latter is based on the premise that compact urban land better preserves open spaces and reduces public services and infrastructure costs than dispersed residential land use pattern.

The remainder of this paper is structured as follows. Section two presents the rationale behind coupling the results of spatial optimization with agent-based simulation. Sections three and four present the conceptual overview of MOLA and ABM implementation. Sections five and six introduce the computational experiment and outline the procedure of model aligning. The closing sections of the paper – seven and eight – summarize the outcomes of computational experiments and the resultant land use implications.

2. Using spatial optimization and agent-based simulation for modeling land use change

According to O'Sullivan and Haklay (2000), Verburg (2006) and others, a purely bottom-up or top-down modeling is insufficient to represent a complex land use system. A generative bottom-up simulation poorly accommodates the regional-scale development objectives. Then, in a top-down simulation, the model variables and mechanisms represent aggregated quantities rather than actions of individual entities, who are the major decision makers of the land use system. One way to address these deficiencies is to use a combination of both perspectives (Table 1). In this paper, we propose to utilize a regional-scale top-down multiobjective land use allocation, which is loosely coupled with a local-scale bottom-up agent-based simulation (Brill 1979, Duh and Brown 2005, Harris 2001, Tomlin 1990, Ward et al. 2003, Verburg and Overmars 2009).

[Insert Table 1 about here]

With MOLA, the model allocates integrated wholes to land based on elucidated pattern objectives (Tomlin 1990). This normative scenario generator allows for semi-automated design of different yet efficient land use blueprints, where the outcomes obtained are congruent with the objectives contained in the model. The use of objectives and constraints representing spatial criteria of compactness, contiguity, and proximity allows for generation of land use patches of a desired size and shape (Brookes 1997, Herwijnen and Rietveld 1999).

Yet, patterns created by the optimization model represent static allocations of land use and do not incorporate the decision making dynamics of the land use system actors (Verburg 2006). The prescriptive role of spatial optimization can be therefore strengthened by a complementary process-oriented modeling of the land use change drivers. We propose to address these non-linear processes using an exploratory ABM.

In essence, ABM is a bottom-up dynamic structure. Its higher level constructs, like land use patterns, are derived in a bottom-up manner as products of collective behavior. These land use computational laboratories allow for conducting multiple experiments with various configurations of heterogeneous behaviors (Casti 1999, Parker et al. 2003). Due to its ability to simulate individual decision-making and the resulting interactions, ABM has a potential to better represent aggregated outcomes of individual decisions than other modeling approaches (Ligmann-Zielinska and Jankowski 2007). Moreover, if our aim is to evaluate the effects of alternative policies on individual decision making, an ABM is complementary to top-down land use allocation modeling.

The use of MOLA and ABM as complementary modeling methodologies for sustainable land use analysis has two major advantages (Table 1). Firstly, it attempts to represent interactions between institutions and their clients at two levels of granularity (Castella et al. 2007, Verburg 2006): institutions at one level (for example, zoning regulations of local planning agencies) and individual agents at another (for example, developers). The objectives of planning agencies are substantially different from those of property developers and thus merit separate model representations (Fisher 2005). Secondly, the proposed modeling approach compares static form with dynamic process, where the solutions of MOLA are grounded in the realm of ABM-simulated human decision making concerning land development decisions.

The MOLA-ABM approach aims at clarifying issues that are likely to surface in public policy debates (Agarwal et al. 2002). In the case reported below, the models help to evaluate tradeoffs between urban compactness at the regional scale and local land development suitability assessment.

Together, MOLA and ABM are two aligned models employing the same objectives and developed for the same situation. Sensitivity analysis of outcome distribution may indicate to what extent individual decision making is important for creating efficient land use configurations.

Both MOLA and ABM utilize three quantifiable land allocation goals representative of sustainable development principles: economically viable land use change, livable and attractive neighborhoods, and easy access to urban activities like retail stores and schools. These goals are translated into MOLA-ABM correspondence rules, where the selected sustainable land development principles decode into MOLA objectives and analogous decision criteria used by agents in evaluating spatial options. Despite the similarity of objectives in MOLA and ABM, preferences attached to the objectives may differ between the two models as MOLA's objectives align with preferences of a planning agency and ABM's objectives with preferences of developers.

3. Multi-objective land use allocation: model formulation

The presented MOLA is a simplified version of a model developed by Ligmann-Zielinska et al. (2008). The major objective of this model involves an efficient distribution of urban development over feasible sites in order to meet growth demand and maintain spatial constraints of compactness and contiguity. The model is formulated using a raster data format, where the land use of each cell can be in one of two states: developed (urban) or undeveloped (rural, forested etc.).

Consider the following notation:

i, j	Locations of undeveloped cells ($i, j \in U$ where U is undeveloped land)
v_j	Composite (multicriteria) land value of location *j*
a_j	Composite (multicriteria) attractiveness of location *j*
n_j	Composite (multicriteria) accessibility to the nearest development for cell *j* (nearness of location *j*)
d	Estimated total demand for new development
M_j	Undeveloped neighborhood of location *j* (in this study, neighborhood is composed of 3x3 cells centered at *j*)
s_j	Number of already developed cells within *j*'s neighborhood
b	Minimum required number of cells in the neighborhood that are developed after allocation

Variables:

x_j	Equals 1 if undeveloped land at location *j* becomes developed; 0 otherwise

Maximize

$$\sum_j v_j x_j \qquad (1)$$

$$\sum_j a_j x_j \quad (2)$$

$$\sum_j n_j x_j \quad (3)$$

Subject to

$$\sum_j x_j \geq d \quad (4)$$

$$s_j + \sum_{i \in M_j} x_i \geq b x_j; \forall j \quad (5)$$

$$x_j \in \{0,1\} \quad x_i \in \{0,1\} \quad (6)$$

The first objective encourages new development on potentially the most valuable land. The aim of the second objective is to maximize the number of the most attractive areas from a given planning perspective. The third objective maximizes the accessibility to current development. Assigning variable importance to the three objectives allows for tradeoff assessment among the sustainable land use premises outlined above. Constraint (4) guarantees that the demand for new development is satisfied. Inequality (5) represents an infill constraint called a density based design constraint (DBDC). Finally, formulations (6) guarantee that the decision variables are binary.

DBDC allows for allocation to cell j if and only if the sum of the j's initially and newly developed neighbors is at least equal to the threshold value b. Therefore, the higher the value of b in this constraint, the more compact and contiguous is the pattern obtained, preventing leapfrog development (Ligmann-Zielinska et al. 2008). In the scenarios reported here, we set b=1 (see section 7).

3.1 Generating different alternatives

To account for varying viewpoints of potential stakeholders, the set of proposed land use blueprints should encompass more than one feasible option (Harris 2001). Moreover, the generated scenarios should be sufficiently different from each other to provide distinct or even contrasting visions for future development.

To address this goal, we extended the model with a specific generative method called Hop-Skip-Jump (HSJ), which was developed by Brill et al. (1982). The HSJ approach is a two-stage process. In the first step, the original model, described above, is executed to produce a 'reference' scenario that provides two types of initial output: [1] a set of variable values split into land that is still undeveloped ($x_j = 0$), and newly developed land ($x_j = 1$, hereafter referred to as a *K*-set), and [2] model objective values. The latter are further used as acceptable performance targets for subsequent solutions (Ligmann-Zielinska et al. 2008). In the second step, a new model (M_n) is derived from the original model, in which the original objectives are converted to constraints assuring that any subsequent solution will perform at least as good as user-defined percentage of the initial objective function value (F). We define the objective of M_n as minimization of *K*-set, forcing the model to pick the current zero-value variables to become positive in order to obtain the best objective score. Consequently, in the MOLA model presented here, the target values for initial objective F are equal to $F+fF$, where f is a user-defined relaxation within a range [0, 1.0]. If $f = 0$ the model looks for an alternative noninferior solution that is different from the initial result. If f is slightly larger than 0, we end up with close-to-optimal solutions that, given the solution space, have a spatial pattern different from the initial allocation map.

4. Agent-based model of residential development: model formulation

Developer agents operate on a cellular (raster) space, in which each cell is characterized by three land attributes that correspond to MOLA objectives: land value, land attractiveness (scenic beauty), and land accessibility. The agents have demand for land, preferences (expressed by decision weights) for the three land attributes, perceptions represented as attitudes to risk related to the return on property investment, and disutilities reflecting agent dissatisfaction from lost investment opportunities. The reported ABM uses a risk-explicit approach to decision making, in which agents are governed by nonlinear attitude utility functions that epitomize developers' perception of risk related with the property investment (Ligmann-Zielinska 2009). The utility functions, proposed by Kemeny and Thompson (1957), reflect people's psychological attitudes to gaming. Specifically, given the utility of an option represented by some measure of performance, the nonlinear functions bend the linear relationship between the criterion value and option utility, so that the perceived value is either higher (overestimated) or lower (underestimated) than the true value. The agents make decisions based on ordered choice heuristic (Benenson and Torrens 2004), which utilizes a customized Ideal Point (IP) decision rule modified to account for these different attitudes to risk. Details of the choice algorithm are presented in Ligmann-Zielinska (2009).

Agents enter the landscape at the beginning of the simulation. Each agent draws a sample of developable locations, which are evaluated using the IP decision rule. With the utilities of sites calculated, the agent orders the options from best to worst to arrive at an investment set.

To match the land units of simulation with the land units of decision making, which are often composed of several pixels (Verburg 2006, Robinson and Brown 2009), we extended the ABM with a clustering algorithm that is equivalent to DBDC in MOLA. An agent selects from the investment set a seed cell j around which it builds a 3x3-size cluster of potential development.

This cluster is the maximum piece of compact land comprising one cluster plan. In the next step, the agent checks all cells in the cluster and removes any undevelopable locations, creating a cluster plan M_j (section 3). The agent prefers compact development, but at the same time is constrained by the availability of developable land in the cluster. Similarly to the DBDC constraint in MOLA, if b=1, at least one developed cell must be present in M_j for it to be considered in further investment process. The reason for the adoption of the clustering mechanism in ABM is the practice of land development, in which developers prefer contiguous land parcels over disjoint and fragmented parcels. This preference is driven primarily by the cost of land development, which, all other cost factors being equal, is lower for contiguous land parcels. Moreover, this mechanism allows for compactness consistency between the two models. Note that M_j can be a partial cluster, which is a neighborhood composed of less than 9 cells. The clustering algorithm is repeated as long as the demand for land remains unmet. The pending investment plan of a given agent is composed of a collection of (partial) clusters. The investment plan is initially pending because some of the locations in clusters may be selected by more than one developer agent, causing a conflict among them. To resolve such conflicts, we introduced a utility-based bidding rule that compares the scores among the overlapping clusters. The agent who assigned the highest cumulative utility to their cluster acquires this cluster together with the disputed locations. Consequently, other developers remove all their overlapping clusters from their investment plans. To satisfy their respective demands, they need to revisit updated investment sets (with the cells from the disputed overlapping clusters excluded from further analysis) and build additional clusters. Furthermore, the utility of each lost cluster is added to agent's disutility D. Therefore, in a highly competitive market, where agents are provided with limited developable land, D should be relatively high.

The outlined investment process continues until all conflicts are resolved and all demand for growth is satisfied, at which time the sites from investment plans are converted to ‘developed’ and the model starts another time step. Unlike other developer ABMs (Devisch et al. 2009, Saarloos et al. 2005), our model does not simulate negotiation, but rather focuses on bounded rationality, expressed through an imperfect knowledge about developable locations. This property market feature may be especially relevant to the studied exurban region, described in the following section.

5. Computational experiment

The example application of MOLA and ABM covers 1,112 square miles located in Central Washington. The area encompasses Wenatchee/East Wenatchee Urban Growth Areas and a few smaller towns like Waterville, Entiat, Cashmere, Leavenworth, and Rock Island, located in Chelan and Douglas Counties, the State of Washington, USA (Figure 1). The Columbia River, which flows from north-east to south-east, divides the area into two geographically distinct parts: the mountainous forested Chelan County region on the west bank of the river (Cascade Mountain Range) and the rural, mostly flat Douglas County area that lies east of the river.

[Insert figure 1 about here]

The choice of the study area was dictated by a number of reasons. First of all, the region is spatially differentiated and, at the same time, has a computationally feasible size. Moreover, the region’s growth distinguishing features contain three competing forces which have a direct consequence on future development of the locality: protection of unique salmonid habitat, highly prioritized agriculture, and seasonal influx of people from metropolitan areas in the western part of Washington State (City of Chelan 2000, Douglas County 2007). Hence, efficient, compact, and contiguous urban land use patterns are important for any sustainable growth plan of the region.

The analysis was performed using a 2-dimensional raster data format with a cell resolution of 4 acres (~127 by 127 meters) and the extent of 459 columns by 389 rows. The database inventory comprised a number of primary layers including current land cover, elevation, roads, cities, soil building potential, preserved land, and census data for block groups. The data was collected between 2000 and 2002 from a variety of sources including county governments, Office of Financial Management for the State of Washington, and national data clearinghouses. The list of data layers and geoprocessing operations carried out to compile the model database is included in appendix A. The data layers were used to produce composite spatial criteria using the linear combination method within GIS (Randolph 2004). The following characteristics of the locality were derived (Figure 2): current development, land value, land attractiveness, and land accessibility.

[Insert figure 2 about here]

The demand for land during the 2000 – 2025 period , estimated to be 18000 acres and represented by 4500 new 4-acre urban cells, was linearly extrapolated from data for the year 2000. Steps of the estimation procedure are presented in appendix B. We assumed that all demand would be accommodated. This assumption was justified based on the building permit activity between 2000 and 2006. Although, during that time, the number of permits increased 1.6

times for both counties, the vacancy rate did not change, suggesting that all new dwellings were absorbed by the market.

Since the permits are issued yearly, we assumed that one year would be an appropriate time step for the agent-based simulations. Within the ABM, the demand for developable land was equally distributed among three developer agents. Each model was executed for 25 time steps representing 25 years. Each time step every developer agent scans a randomly drawn 15% sample of all currently available undeveloped cells (Brown and Robinson 2006).

6. Methodology of output coupling

The research reported here involves two stages of experimentation: generating MOLA blueprints followed by ABM simulations with selected MOLA maps superimposed as zoning constraints. The post-processing analysis of MOLA results concentrates on evaluating the magnitude of development clustering using the following aggregate fragmentation statistics calculated with Fragstats 3.3 (McGarigal and Marks 1995): number (count) of developed patches (NP), largest patch index (LPI, the percentage of the landscape occupied by the largest developed patch), mean nearest neighbor (MNN, mean of Euclidean distances calculated from a given developed land patch to its nearest neighboring patch), and aggregation index (AI, the number of like adjacencies involving the developed land, divided by the maximum possible number of like adjacencies involving the developed land, given in percentage). This analysis aims at designing UGAs composed of compact clusters in conformance with the Growth Management Act of the State of Washington (City of Chelan 2000, Douglas County 2007). Therefore, a preferred MOLA plan should minimize NP and MNN and maximize LPI and AI.

As outlined in section 3.1, another goal of MOLA is to provide alternative land use blueprints. Therefore, in order to assess the morphological disparity among maps on a cell-by-cell basis (Gustafson 1998) we utilize the following pairwise map difference statistic (PMD):

$$Map_{Dif} = \frac{d_c}{2 * d_{tot}} * 100\% \qquad (7)$$

Where d_{tot} is the total allocated demand and d_c is the number of cells that are undeveloped in one map and developed in the other. As an illustration, suppose that the demand for new development is 15 cells. With this demand, the maximum theoretical difference between the two maps equals 30, which is equivalent to the case where every land use unit is allocated to two different cells in the maps. Assuming that the observed difference between maps is 18 cells, Map_{Dif} equals 60% (18/30 *100%).

As a result of MOLA outcome evaluation, two different maps are selected, named MOLA1 and MOLA2, respectively. The selected maps have comparable composite objective function values, and, at the same time, they have the maximum pairwise difference among all of the generated plans. What follows is ABM experimentation that aims at assessing the impact of DBDC clustering and the influence of the two MOLA plans on total agent disutility. The major goal of ABM computational experiments is to determine a consensus planning scenario, in which the agent disutility caused by reduced supply of developable land is minimized without compromising the compactness of UGA.

Table 2 summarizes the ABM experimental design. The experiments exploit four input factors, which are either varied or set to constant values: attitude heterogeneity (A-het), preference heterogeneity (P-het), the degree of clustering (DBDC, b=0 or b=1) and input developable land zoning (M-dev). A-het forms a discrete set comprising different combinations of risk attitudes including risk-aversion, risk-indifference, and risk-taking. P-het draws one of the weight vectors presented in Table 3. M-dev contains a set of input land use maps, including the initial developable map, MOLA1, MOLA2, and different MOLA1/MOLA2 relaxations.

[Insert Table 2 about here]

[Insert Table 3 about here]

In the free market base experiment (1), agents are unaware of the MOLA zoning regulations. Their decision making is driven by their attitudes, preferences, and access to knowledge about opportunities for development. Exp2 and exp3 are the modifications of the baseline case, in which various combinations of the less constraining DBDC b=0 and the more constraining DBDC b=1 are studied.

In the MOLA cases (exp 4 to exp7), agents are forced to obey the slightly relaxed MOLA constraints (expanded with a 1-cell ring to assure computational feasibility), which substitute for the initial input developable land layer.

To evaluate the impact of MOLA zoning on agent disutilities, we decided to further relax the blueprints with various distance buffers created around the MOLA plans. We started from calculating Euclidean distance to the MOLA boundaries. This distance surface was reclassified so that each buffer ring contained a comparable number of developable cells to avoid the problem of scale dependence. As a result, for both MOLA maps, we created 10 relaxation bands covering the distance range from 127m to ~4km (larger distances were excluded). These relaxation bands were further used as input land use maps in exp5 (MOLA1) and exp7 (MOLA2).

For ABM experimentation we used Monte Carlo simulation with the Sobol' quasi-random design procedure, which allows for full-range exploration of input parameter space and the subsequent computation of sensitivity indices (Lilburne and Tarantola 2009, Saisana et al. 2005). The ABM was executed for 384 input samples for exp1 and exp2 respectively (two input parameters, see Table 2), 512 samples for exp3, 4, and 6 each (three input variables), and 640 samples for exp5 as well as exp7 (four input variables).

The ABM results were analyzed in three different ways. First, we compared the distributions of outcome maps, agent disutility, and output fragmentation statistics using graphical and statistical analyses. Second, variance-based global sensitivity analysis (GSA) was undertaken (Lilburne and Tarantola 2009). GSA allows for decomposing model output variance and apportioning it to uncertain input factors. The variance decomposition is summarized using two sensitivity indices for every input *i*: first order (Si), and total-effect (STi). The former calculates output sensitivity due to *i* variability treated individually, whereas the latter analyzes model sensitivity to *i* in combinations with other input variables. Since the ABM is nonlinear in nature, the use of (Si, STi) pairs allows for detecting factors that play a significant role in outcome variability as well as calculating the magnitude of their interactions. With GSA, we determined the influence of preferences, attitudes, DBDC and the relaxed MOLA plans on development clustering and agent disutility. GSA was calculated with SimLab – an open source software (http://simlab.jrc.ec.europa.eu/).

The final stage of the post-processing analysis aimed at finding a compromise solution that would satisfy both clustering maximization and disutility minimization objectives. For exp5 and exp7, we plotted selected fragmentation statistics against disutility for different MOLA bands, searching for MOLA relaxations that best expressed the compactness-disutility tradeoff.

7. Results and analysis

Preliminary MOLA calculations did not allow for DBDC's b>2 (Equation 5). Values of b>2 resulted in infeasible model solutions. Since the difference between b=1 and b=2 in terms of outcome compactness was negligible, in the experiments that followed, we fixed b=1 and focused on generating solutions by varying the objective weights presented in Table 3.

We used the weighting method proposed by Cohon (1978) to aggregate the three objectives into one. Overall, given one initial model execution and one HSJ iteration, we performed 14 model runs, two for each objective weight vector (Table 3). The objective values that were used in the HSJ iteration were relaxed by 5% (f=0.05, section 3.1). The model was solved using CPLEX Mixed Integer Optimizer (ILOG, http://www.ilog.com) on a SunBlade 2500 dual processor (467MHz each) workstation with Solaris 7.1 operating system. Default settings were used and no attempt was made to optimize performance.

7.1 MOLA results

Table 4 presents fragmentation statistics of MOLA outcome maps. The particular weight scenarios are symbolized using three sequential digits for land value, land attractiveness, and land accessibility, respectively. For example, '442_ini' denotes an initial MOLA formulation, where *land value* has a weight of 0.4, *attractiveness* weight is set to 0.4, and *accessibility* weight equals 0.2, whereas '442_1' is the same weight scenario for the HSJ iteration. Because MOLA does not limit the emergence of plans that do not fit the development constraints that are not part of the model (like the willingness of land owners to sell their land), we excluded MOLA solutions that did not fit the realities of the region as outlined in the Countywide Comprehensive

Plans (Douglas County 2007). Consequently, the final collection of land design blueprints was composed of 13 maps.

[Insert table 4 about here]

The best results concerning the spatial pattern metrics occur for the 244 weight scenarios. For MNN and LPI fragmentation measures the *initial 244* MOLA achieves the best results (2.66 and 3.12 respectively). For NP and AI measures *244 HSJ* iteration scores the best (2083 and 60.42 respectively.

For the 13 MOLA outputs, 78 pairwise combinations can be obtained (n/2*(n-1), where n=13). These map pairs were used in calculating the level of development allocation difference (represented by PMD statistic given in Equation 7). PMD varies between 11.76% and 95.76% of the maximum theoretical difference. On average, the maps differ by 4685 cells (52%) with a considerable variability among the pairs (*cv*=0.4). Interestingly, most of the differences that exceed 77% occur for one of the 244 weight schemes.

Therefore, we selected the *initial 244* scenario (named MOLA1) and the *HSJ iteration 244* scenario (named MOLA2) as zoning plans used in ABM experimentation. PMD for these maps equals 94.96% as compared to the maximum possible difference, meaning that almost every unit of land demand is allocated to one site under MOLA1 and to a different site under MOLA2.

Figure 3 illustrates the selected maps superimposed on each other. In general, MOLA1 allocates growth evenly within the valleys. Specifically, new development clings to current urban areas like the small towns in the valley of the Wenatchee River or the Greater Wenatchee Urban Area.

Moreover, the arrangement of growth in MOLA1 represents a closer approximation of the development pattern proposed in local comprehensive plans and zoning regulations.
Contrary to MOLA1, the pattern in MOLA2 is much less scattered and concentrates in two emerging roundish areas: the town of Waterville in the north-east corner of the study area, and the northern part of the Greater Wenatchee Urban Area. The former urban cluster is an especially novel alternative to the current zoning.

[Insert figure 3 about here]

7.2 ABM results

We started from mapping the frequencies of land use change averaged per cell and calculated for each experiment separately. Figure 4 shows the most visually differing configurations for two areas within the region: northern part around Waterville (column 1), and Wenatchee UGA (column 2).

[Insert figure 4 about here]

Visual exploration of the patterns reveals an influence of MOLA plans on the resulting spatial variability. The baseline experiment exhibits the most scattered development, which can be explained by the omission of DBDC and MOLA plans. The growth is less adjacent to the existing urban patches and can be seen in rural places as well. Specifically, new development is scattered along the Columbia River valley.

Exp4 and 6 show the most compact development that, over time, glues to towns or produces new urban clusters. As expected, land use patterns resulting from exp4 and 6 resemble their respective MOLA plans. Moreover, the *relaxed MOLA1* experiment (5) approximates its more restraining version (exp4). Interestingly however, for MOLA2 exp7 differs considerably from exp6. Specifically, for the Wenatchee UGA, exp7 is closer in shape to exp1 than to exp6. We hypothesize that MOLA2 is very limiting from the perspective of bottom-up decision making. If the agents are provided with other development alternatives (like in the more relaxed exp7), they avoid many of the locations imposed by MOLA2.

Next, we focus on analyzing the magnitude and significance of uncertainty characterizing ABM outcome fragmentation. The distributions of total agent disutility (*D*) and outcome fragmentation statistics (NP, LPI, MNN, and AI) are shown in Figure 5.

[Insert figure 5 about here]

The differences in *D* among experiments are relatively moderate. The means fluctuate within the 100-150 range with higher values observed whenever the restricting MOLA characteristics (MOLA plans or DBDC b=1) are imposed on agents (exp2, 4, 6). Observe that MOLA relaxation (exp5 and 7) results in *D* comparable to the free market case. One-way ANOVA was conducted to further compare the differences in *D* among ABM experiments (PASW Statistics http://www.spss.com/, see Table 5). The results of ANOVA show that the variation in disutility among different ABM conceptualizations is significantly higher than random. Recall that *D* quantifies the intensity of conflicts among agents. Thus we can conclude that the inclusion of

MOLA constraints (both the final MOLA plans and DBDC b=1) increases market competitiveness.

[Insert table 5 about here]

From the planning agency perspective, the increase in land compactness and contiguity is the most desirable output. In terms of NP and AI, experiments 2, 4, and 6 score the highest (Figure 5), with the fragmentation statistic values somewhat better than either of the selected MOLA maps (Table 4). Interestingly then, local decision making produced by ABM generates a slightly less patchy pattern than the top-down multiobjective land allocation.

When ABM results are compared with the MOLA plans, LPI is the most surprising statistic. For exp4 and exp6, the ABM generated plans give much better LPI scores (~12) than the MOLA maps alone (2-3).After the additional analysis, we discovered that under highly competitive market conditions (experiments 4 and 6) agents preferred locations close to well established urban areas, which resulted in higher LPI. Since this characteristic has not been coded into the model, we postulate that this is an emergent feature of the ABM that deems future study.

MNN behaves quite differently from the other spatial metrics. The best values can be observed for experiments 5 and 7, implying a more complex relationship between MOLA and the average distance among clusters. We conclude that MOLA relaxation can improve development contiguity by maximizing the closeness of neighboring clusters.

Similarly to agent disutility, we followed the descriptive analysis of fragmentation with ANOVA to determine whether the experiments were statistically significantly different from each other (Table 5). Again, the results of ANOVA suggest a significant impact of MOLA constraints

(MOLA plans and DBDC b=1) on land use fragmentation. Both disutility and pattern metrics were also subjected to power analysis to evaluate whether the observed relationships are substantively important. Cohen's *f* (Table 5) indicates medium to large effect size among the ABM formulations, with the variability of disutility less pronounced than the fragmentation statistics. We infer that, given the moderate variability of disutility, the search for a compromise between the agents and the planning authority should focus on scenarios with the least dispersed development.

7.3 Global sensitivity analysis of ABM output

GSA reveals which input variables are important in determining the outcome variability, and specifically, which factors play a major role in establishing the variance of agent disutility as well as the uncertainty of pattern fragmentation. Figures 6a and 6b illustrate the relative sensitivities of ABM results for D, NP, LPI, and AI for the most differing experiments (exp 2 and 3 have their sensitivity measures very similar to exp1, and exp5 has sensitivities that are very similar to exp7).

[Insert figures 6a and 6b about here]

The visual inspection of GSA results reveals that the variability in agent disutility is mostly defined by the uncertainties in preferences and attitudes to risk. While the *relaxed MOLA* experiments (5 and 7) produce in general lower *D* values (Figure 5), the variance of these disutilities is not affected by the variability of MOLA relaxation, since the 'input developable map' factor is practically nonexistent in the decomposed uncertainty of *D* (Figure 6a).

Consequently, lower values of disutility are a direct effect of MOLA relaxation zones, regardless of the uncertainty related to other input variables. Interestingly, the variance in disutility is predominantly influenced by interactions among inputs (the white portion of Si pies in Figure 6), strengthening the complex influence of attitude on individual decision making (Ligmann-Zielinska 2009).

When analyzed from the perspective of fragmentation variability, the ABM experiments demonstrate an interesting behavior. Recall that the inclusion of MOLA plans into ABM simulations (exp4 and 6) causes a considerable increase in LPI values, which are higher than the corresponding values in MOLA plans alone (MOLA1 and MOLA2, section 7.1). Observe that, for these two experiments, LPI is also extremely sensitive to interactions among inputs (Figure 6b). This corroborates our hypothesis that the surprising behavior of LPI is an emergent feature of the model, pertaining to the dynamic interrelationships among its components. Furthermore, the *relaxed MOLA* bands (exp7, Figure 6b) have an overwhelming impact on LPI variance. This can be explained by the nature of this statistic. Note that exp5 and 7 have relatively low and volatile LPI scores (Figure 5). Whenever a larger MOLA relaxation buffer is introduced, the potential for patch fragmentation increases, resulting in a smaller dominant patch. For the NP and AI, the impact of variable zoning is also substantial (0.20 to 0.25).

Finally, the DBDC b-*value* proved to be the most influential on NP changeability (exp4, 6, and 7 in Figure 6a). This is not surprising, since DBDC encourages infill development, potentially reducing the number of urban clusters.

7.4 Concluding observations

The analysis presented in sections 7.2 and 7.3 focused on the overall impact of MOLA characteristics on ABM outcome variability. In this section, we explore the influence of the respective MOLA relaxation bands on agent disutility and land use fragmentation, in order to find a consensus zoning scenario between top-down planning and bottom-up development.

In the previous section we demonstrated that the relaxed zones of developable areas (‘input developable map’ in exp7, Figure 6a) have a negligible influence on disutility (Si=0.00, and STi=0.09 for exp7; Si=0.03 and STi=0.12 for exp5). The plots in Figure 7 lead to a similar observation. In general, *D* is roughly evenly distributed throughout different MOLA-relaxation distances. We tested this hypothesis by performing the analysis of variance for *D* among the distance bands. The results for exp7 ($F(7,632)=1.52$, $p=.157$, F-crit.=2.1) confirm that there are no differences among mean agent disutilities for MOLA relaxation groups. This is not the case for exp5 ($F(7,632)=2.44$, $p = .018$, F-crit. = 2.1). Thus, for exp 7, the minimum relaxation buffer, which extends the MOLA2-delineated developable land with a 250m-wide ring, would suffice to maintain average *D*. Consequently, while the introduction of MOLA2 into ABM matters for disutility variability (Table 5), a minimally extended MOLA2, which is characterized by a relatively high compactness, would result in a relatively low level of agents’ overall disutility, signifying a compromise development solution. On the contrary, different distance relaxations of MOLA1 can affect agent disutility D, making the consensus solution difficult to find using quantitative measures.

[Insert figure 7 about here]

8. Discussion and summary

The modeling approach reported here is designed to bridge efficient spatial planning with individual decision making in order to understand the dynamics of residential development. In summary of this research, a review question can be posed: What has been revealed about the morphology of land use arrangements in the selected study area and how can this be used to deepen our understanding of current exurban growth?

We started the computational experiments from producing a few land use plans using generative multiobjective land allocation (MOLA). The objective of the MOLA model was to construct land use alternatives that are environmentally and economically efficient, spatially diverse, compact and contiguous. The visual and statistical interpretation of these blueprints ended with a choice of two designs constituting the proposed zoning regulations. Although both land designs were generated using the same objective weight vector, the resultant patterns emphasize different land characteristics. MOLA1 development reflects the attractiveness of biophysical amenity factors like forest and water proximity. Therefore, most of the development is pushed west of the Columbia River basin. In contrast, the growth areas in MOLA2 are designated east of the Columbia River, within the Douglas region of the study area, suggesting that flooding frequency, planned land use, soils, and slope buildup suitability are the major considerations for development allocation.

The second stage of computational experiments involved an exploratory agent-based simulation (ABM) that investigated the impact of different MOLA configurations on the competitiveness of local property market. In this respect, the results of one model (MOLA) informed the development of another model (ABM) (Parker et al. 2003).

The developer agents, who represent the decision makers in the ABM, make their choices based on preferences for land value, accessibility, natural amenities, and clustering of development. Agents' partial knowledge of development opportunities generates behavioral inconsistency, resulting in different attitudes to risk that influence individual decision making. Furthermore, the planned investments often lead to competition among agents for the same piece of land. The conflict is resolved based on the overall utility assigned by agents to their respective development plans. As a result, some agents lose their investment opportunities, increasing the total disutility within the market.

As anticipated, the inclusion of MOLA plans into the ABM experiments produces a more compact development, which is tightly clustered around the current settlements. However, this impact is not straightforward. Based on the results of aggregate fragmentation statistics, MOLA configurations did not prove to be notably better than the ABM simulations constrained by them. Thus, we conclude that there is more to compact growth than simple neighborhood infill development, which is the only explicit clustering mechanism in MOLA. Based on the reported experiments, we argue that a consolidation of top-down optimization and bottom-up simulation can be useful in designing development policies that consider not only regional development objectives but also individual goals and behavioral drivers.

The major recommendation from the reported study is the advice on what should not be done in a simulated planning situation (Agarwal et al. 2002). A rigorous enforcement of the proposed MOLA solutions is unadvisable, since the level of clustering improvement may not compensate for the increase in developer disutility. A small relaxation of the MOLA zoning plans could be the best compromise among planning authorities and developers.

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Figure captions

Figure 1 Chelan and Douglas study area, Washington, USA

Figure 2 Normalized composite landscape characteristics used as decision criteria: landuse (developed, undeveloped, and restricted land), land value (mixture of physical, economic, and legal land characteristics that influence land acquisition costs and building construction costs), land attractiveness (closeness to biophysical amenities like water bodies, forests and parks, combined with heterogeneous topography), and land accessibility (Euclidean distance to urban areas and roads)

Figure 3 Difference map between the selected MOLA design blueprints used further in the comparative analysis: [1] development that occurred only in the initial 244 weight scenario (called MOLA1), [2] development that occurred only in the 244 HSJ=1 weight scenario (called MOLA2), [3] initially developed land

Figure 4 Probabilities of development for selected three ABM experiments; [1]: northern region around Waterville, [2]: the Greater Wenatchee Urban Area

Figure 5 Summary box plots of ABM experiments for disutility and selected fragmentation statistics

Figure 6 Input factor sensitivities calculated for ABM outcomes (Si – first order index, STi – total effect index): [a] disutility and number of patches, [b] largest patch index and aggregation index. White color wedge of Si represents the interaction effect, that is, a fraction of output uncertainty that cannot be explained by individual input factors.

Figure 7 Correlation between disutility and selected fragmentation statistics for experiment 7, grouped by initial developable locations, which are defined by distance-based relaxation of the MOLA2 plan (exclusionary zoning).

Tables

Table 1 Selected characteristics of multiobjective land allocation – MOLA, agent-based modeling – ABM, and the consolidated MOLA-ABM

Model	Advantages
MOLA	Semi-automated design
	Prescriptive top-down modeling
	Non-dominance of solutions
	Regional-scale aggregate development allocation
ABM	Explicit inclusion of individual decision making
	Exploratory bottom-up modeling
	Symbolic representation of society
	Local-scale individual-level development
Both models	Decision making dynamics tested against the proposed zoning blueprints
	Static form and dynamic process
	Multiple compromise spatial solutions
	Comprehensive policy modeling

Table 2 Input factors used in seven ABM experiments: V – variable, F – fixed at a constant value, M-dev: input developable map, A-het: heterogeneous attitude to risk, P-het: heterogeneous preferences (weights), DBDC: clustering constraint; when DBDC is variable (V) it means that some agents have b=0 and other agents b=1, ini: initial input land use map, MOLA1: selected MOLA result 1, MOLA2: selected MOLA result 2, V(MOLA) represents different MOLA plan relaxations.

Experiment	M-dev	A-het	P-het	DBDC
Exp1: free market (baseline)	F(ini)	V	V	F(b=0)
Exp2: cluster development	F(ini)	V	V	F(b=1)
Exp3: variable cluster development	F(ini)	V	V	V
Exp4: MOLA1 as input developable land	F(MOLA1)	V	V	V
Exp5: Varying MOLA1 relaxations	V(MOLA1)	V	V	V
Exp6: MOLA2 as input developable land	F(MOLA2)	V	V	V
Exp7: Varying MOLA2 relaxations	V(MOLA2)	V	V	V

Table 3 Objective weight vectors in MOLA and agent preferences in ABM

Weights used in both models		**Land Value**	**Attractiveness**	**Accessibility**
1	Equal importance	0.3333	0.3334	0.3333
2	One criterion dominates	0.6	0.2	0.2
3		0.2	0.6	0.2
4		0.2	0.2	0.6
5	One criterion is less important	0.4	0.4	0.2
6		0.4	0.2	0.4
7		0.2	0.4	0.4

Table 4 Selected fragmentation statistics for the output MOLA blueprints

MOLA scenario	NP	LPI	MNN	AI
Equal_ini	2181	2.23	2.68	57.80
Equal_1	2176	2.46	2.74	59.65
622_ini	2200	2.41	2.70	57.34
622_1	2237	2.45	2.75	57.17
442_ini	2212	2.17	2.71	57.01
442_1	2225	2.68	2.75	57.86
424_ini	2135	2.44	2.70	58.87
424_1	2169	2.34	2.74	58.93
262_ini	2280	2.65	2.68	54.59
244_ini	2141	**3.12**	**2.66**	58.09
244_1	**2083**	2.13	2.69	**60.42**
226_ini	2108	2.42	2.71	59.76
226_1	2114	2.06	2.71	60.17
max	2280	3.12	2.75	60.42
min	2083	2.06	2.66	54.59
avg	2174	2.43	2.71	58.28
std dev	57	0.28	0.03	1.60

Table 5 The significance of differences among ABM experiments calculated for total agent disutility *D* and selected fragmentation statistics. F-crit. = 2.10, α=0.05, degrees of freedom: between groups = 6, within groups = 3577

Statistics	**F**	**Sig.**	**Cohen's f**	**Effect size**
D	50.4	0.000	0.29	medium
NP	883.6	0.000	1.22	large
LPI	5362.4	0.000	2.99	large
MNN	214.3	0.000	0.60	medium/large
AI	490.1	0.000	0.90	large

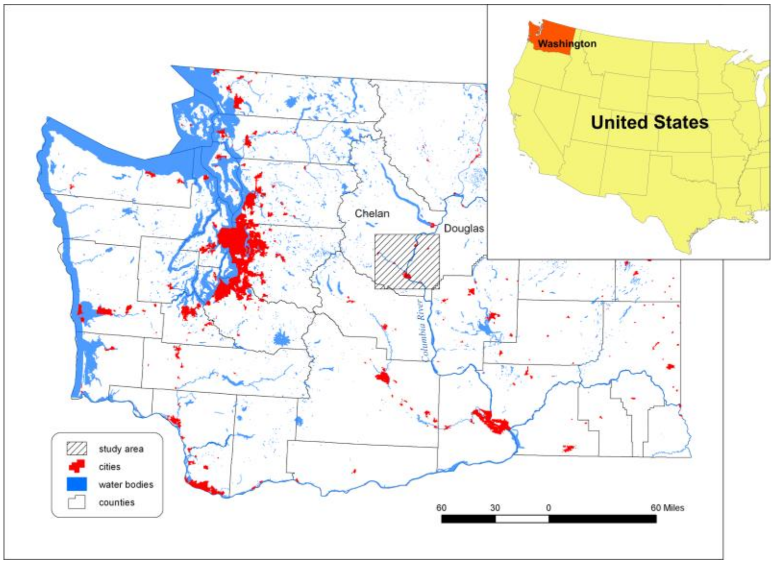

Figure 1

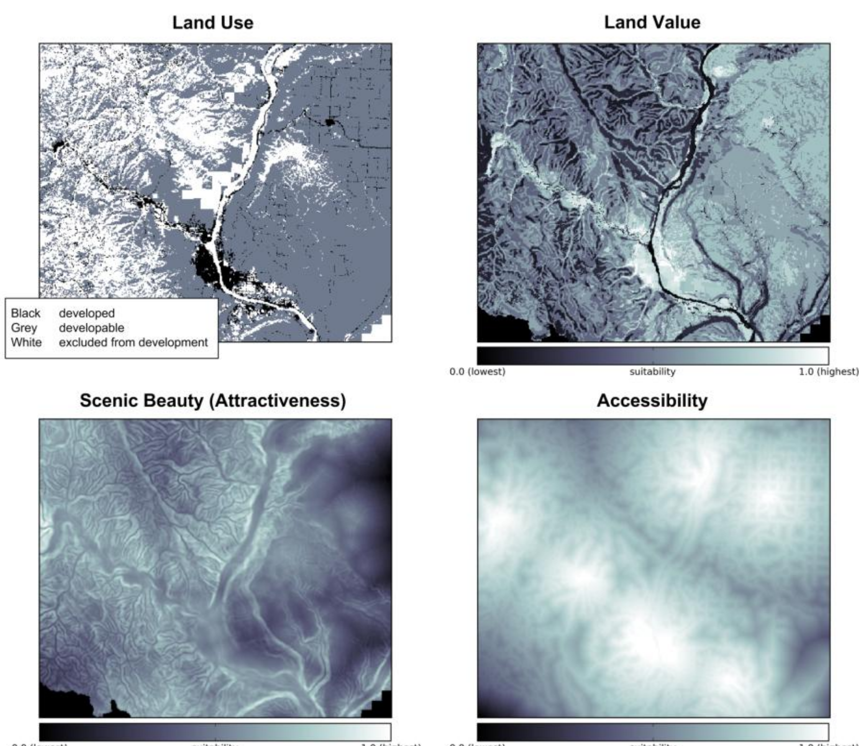

Figure 2

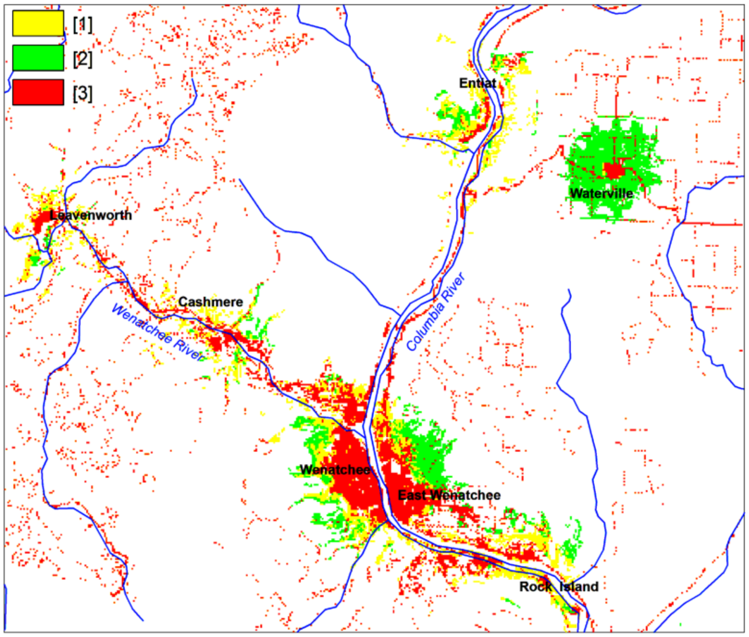
[1]
[2]
[3]
Entiat
Waterville
Leavenworth
Cashmere
Wenatchee River
Columbia River
Wenatchee
East Wenatchee
Rock Island

Figure 3

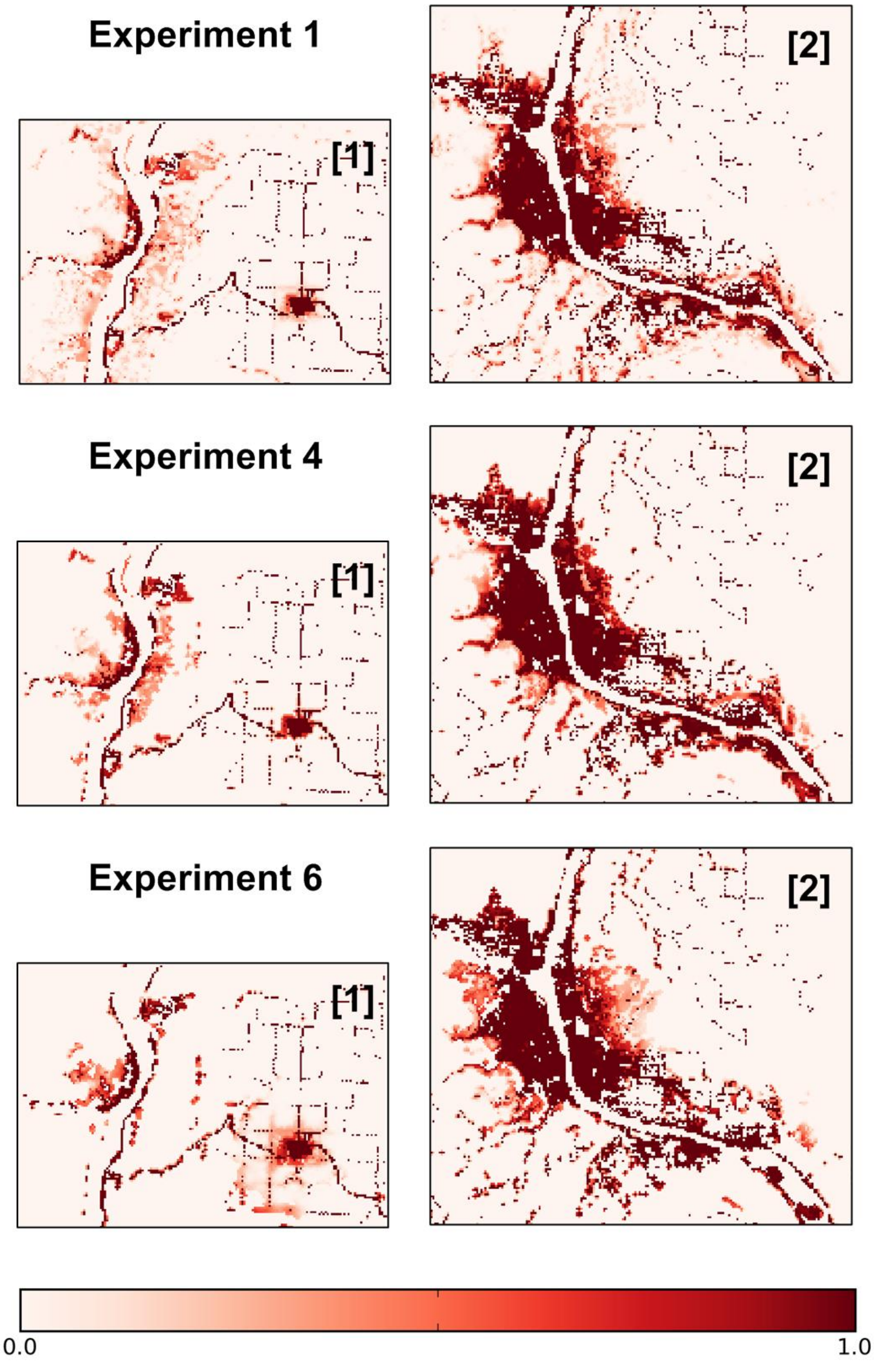

Figure 4

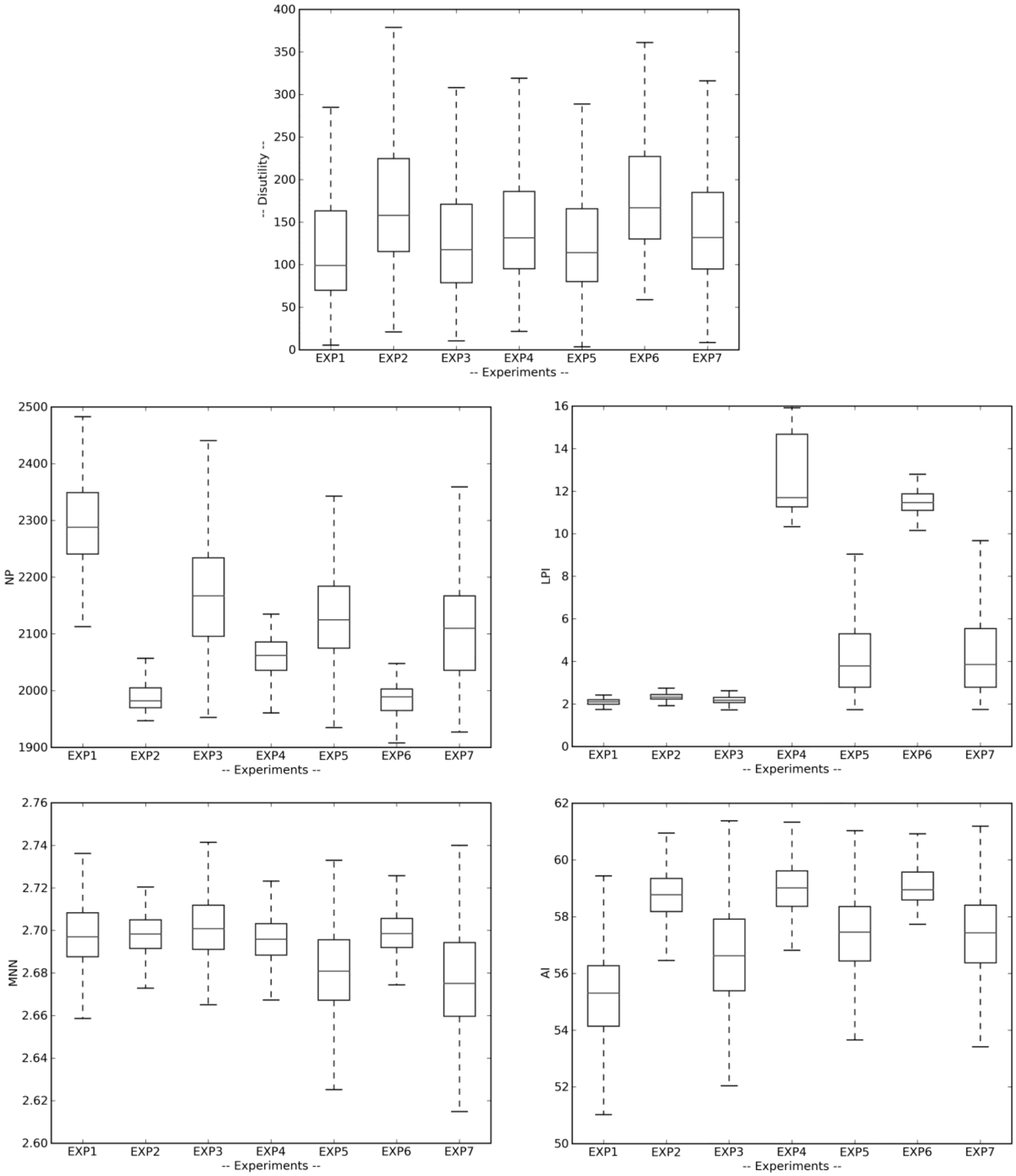
-- Disutility --
NP
LPI
MNN
AI
EXP1
EXP2
EXP3
EXP4
EXP5
EXP6
EXP7
-- Experiments --

Figure 5

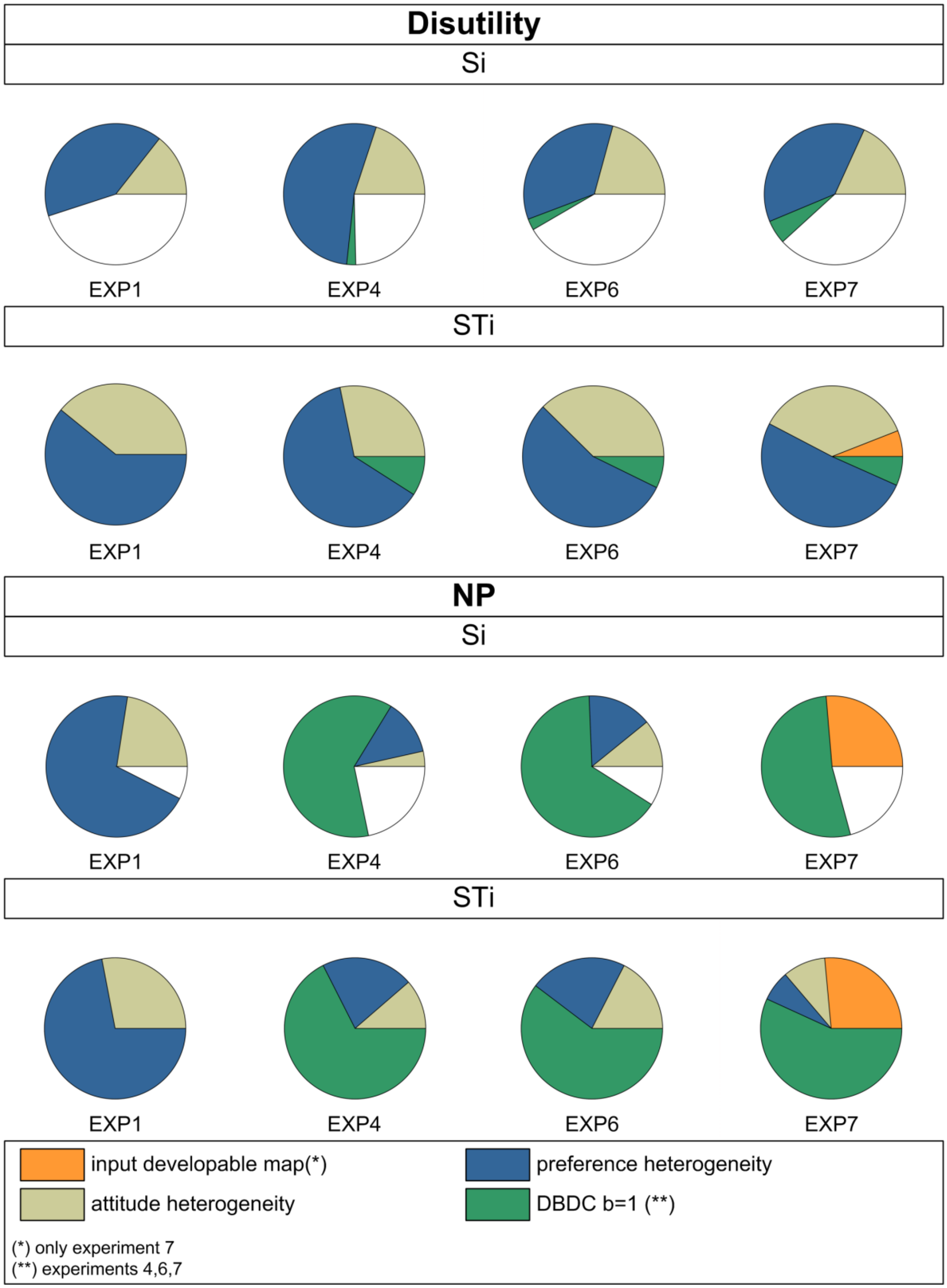
Disutility
Si
EXP1
EXP4
EXP6
EXP7
STi
EXP1
EXP4
EXP6
EXP7
NP
Si
EXP1
EXP4
EXP6
EXP7
STi
EXP1
EXP4
EXP6
EXP7
input developable map(*)
preference heterogeneity
attitude heterogeneity
DBDC b=1 (**)
(*) only experiment 7
(**) experiments 4,6,7

Figure 6a

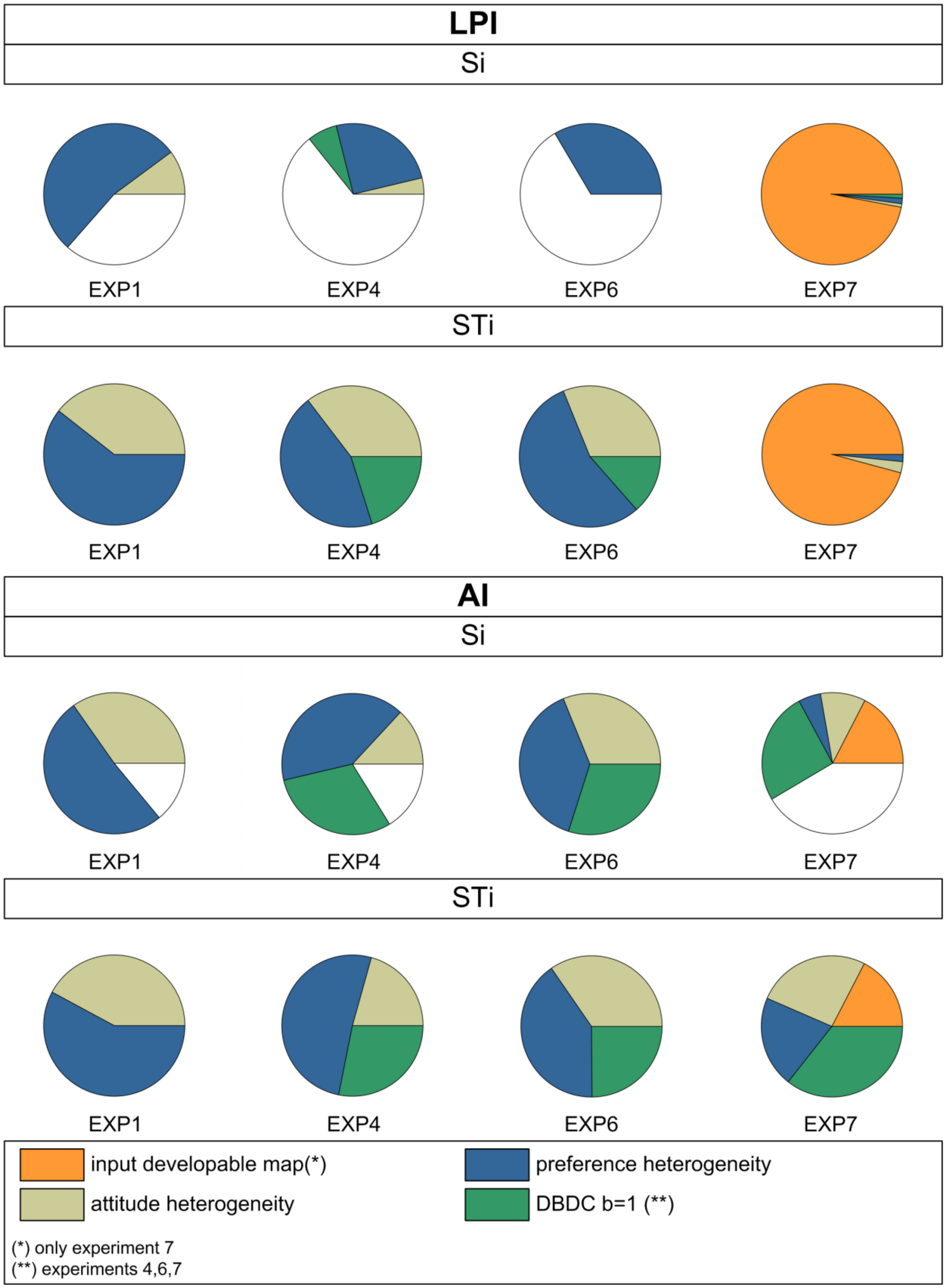
LPI
Si
EXP1
EXP4
EXP6
EXP7
STi
EXP1
EXP4
EXP6
EXP7
AI
Si
EXP1
EXP4
EXP6
EXP7
STi
EXP1
EXP4
EXP6
EXP7
input developable map(*)
preference heterogeneity
attitude heterogeneity
DBDC b=1 (**)
(*) only experiment 7
(**) experiments 4,6,7

Figure 6b

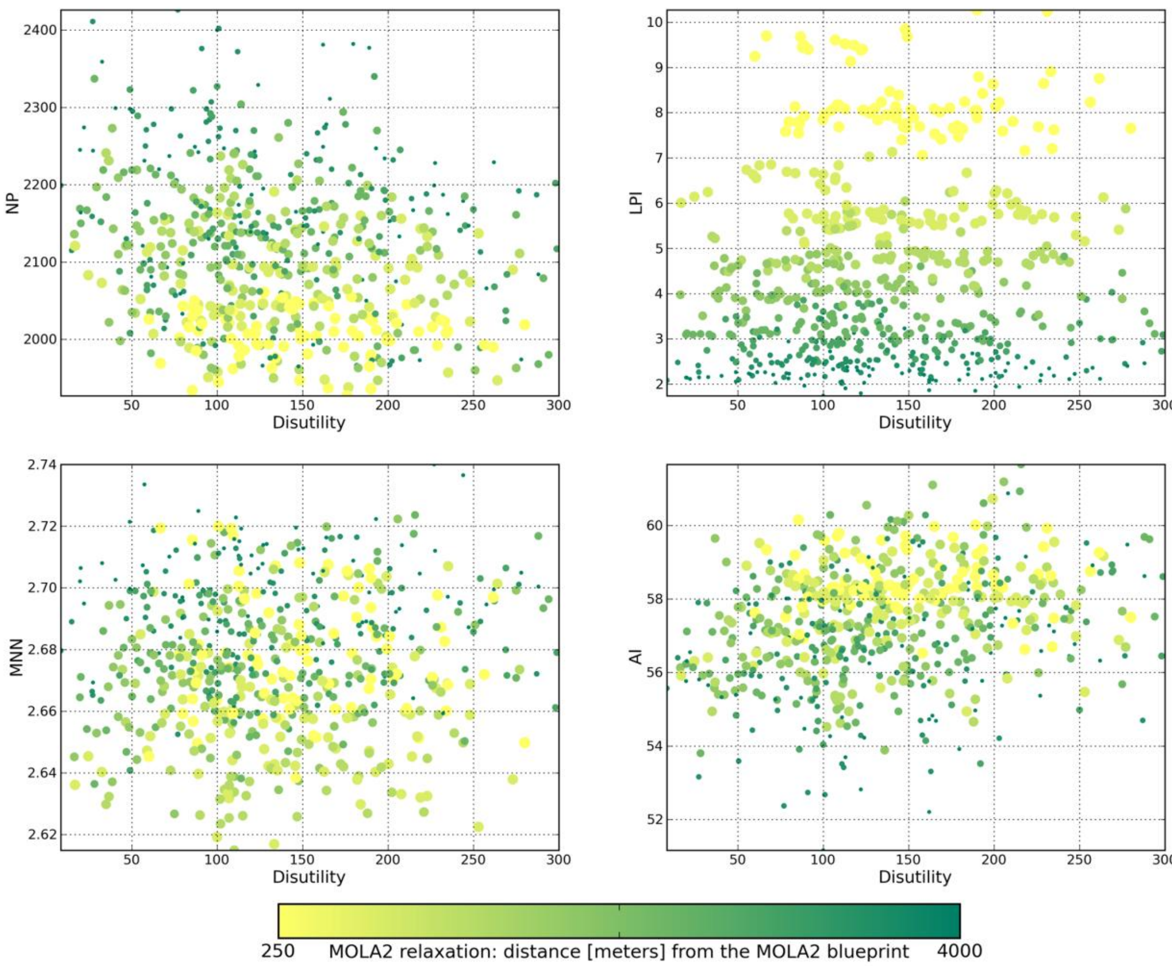
NP
LPI
MNN
AI
Disutility
250
MOLA2 relaxation: distance [meters] from the MOLA2 blueprint
4000

Figure 7

Appendix A

The following tables summarize spatial data preparation steps for the study area (Chelan & Douglas Counties, WA)
All links last accessed: December 2008

<table>
<tr><th>Layer</th><th>Primary Datasets [PD]</th><th>PD Date</th><th>PD Source</th><th>Geoprocessing Procedure</th></tr>
<tr><td rowspan="5">Land Use
Current urban, non-developed, & restricted land uses</td><td>Basic landuse source dataset</td><td>2001</td><td>http://seamless.usgs.gov/
30 meter NLCD resolution Landsat Thematic Mapper and Landsat Enhanced Thematic Mapper satellite imagery</td><td rowspan="5">Selected preservation areas: water, wetlands, orchards, parks, recreation, reservations, wilderness, wood, wildlife refugees, fish hatcheries, golf courses, and glaciers were excluded from analysis.
Additionally, buffered critical fish habitats with 250 feet distance (according Chelan City Comprehensive Plan category I wetlands)
The resultant grid was set to 4 acres resolution</td></tr>
<tr><td>Critical fish habitat for restricted areas</td><td>~2000</td><td>http://www.nwr.noaa.gov/</td></tr>
<tr><td>Douglas parks and recreation areas</td><td>2003-2007</td><td>ftp://ftp.douglascountywa.net/</td></tr>
<tr><td>Landmarks</td><td>Census 2000</td><td>http://www.esri.com/data/</td></tr>
<tr><td>Public lands</td><td>~2000</td><td>http://www.dnr.wa.gov/</td></tr>
</table>

Accessibility Easy and proximate access to various urban activities (land uses) like services, retailing etc.	Cities (distance to urban areas)	2002	http://www.wsdot.wa.gov/	Calculated straight line distance surface and normalized the distance layer so that higher & better values represent areas closer to cities
	Detailed roads	Census 2000	http://www.esri.com/data/	Calculated straight line distance surface and normalized distance layer so that higher & better values represent areas closer to roads
	Combined the two derived rasters using the weighted summation aggregation function. Three weight vectors were considered: {0.3,0.7}, {0.7,0.3}, {0.5,0.5}. The resultant layers had a min correlation of r=0.83 with 99% significance, therefore picked a layer where the weight of distance to cities = 0.7 and the weight of distance to roads = 0.3, which was justified by the fact that human activities (services, industry etc.) take place in cities and not on roads. Moreover, the road network in the area is dense and spatially quite homogeneous.			

Attractiveness Closeness to water bodies and forest combined with heterogeneous topography	Basic landuse source dataset (water land cover)	2001	http://seamless.usgs.gov/ 30 meter NLCD resolution Landsat Thematic Mapper and Landsat Enhanced Thematic Mapper satellite imagery	Calculated straight line distance from the water surface and normalized the distance layer so that higher & better values represent areas closer to water
	Basic landuse source dataset (forest land cover)	2001	http://seamless.usgs.gov/ 30 meter NLCD resolution Landsat Thematic Mapper and Landsat Enhanced Thematic Mapper satellite imagery	Calculated straight line distance from the forest surface and normalized the distance layer so that higher & better values represent areas closer to forest
	Elevation grid	~2000	http://rocky.ess.washington.edu/	Derived slope percent raster and normalized the slope layer so that higher & better values represent steeper slopes
	Combined the three derived rasters using the weighted summation aggregation function. Five weight vectors were considered {forest [f], water [w], slope [s]}: {0.3334,0.3333,0.3333}, {0.6,0.2,0.2}, {0.2,0.6,0.2}, {0.2,0.2,0.6}, {0.5,0.2,0.3} the resulting layers had a min correlation of r=0.8 with 99% significance except for the following pairs (1) 0.6[f], 0.2[w], 0.2[s] versus 0.2[f], 0.6[w], 0.2[s] (r=0.58, 99% significance); (2) 0.2[f], 0.6[w], 0.2[s] versus 0.2[f], 0.2[w], 0.6[s] (r=0.58, 99% significance); (3) 0.2[f], 0.6[w], 0.2[s] versus 0.5[f], 0.2[w], 0.3[s] (r=0.60, 99% significance). Nevertheless, the correlation between the surfaces was never below r=0.58 and it was always positive. Since none of the criteria seem more important than others, the equal weight case was used in further analysis.			

Land Value Influence of physical, economic, and legislative land characteristics on land acquisition costs and building construction costs	Physical Value Soils: soil suitability, flooding frequency Elevation: slope suitability	~2000	Soils: http://soildatamart.nrcs.usda.gov/ Elevation: http://rocky.ess.washington.edu/ http://seamless.usgs.gov/	<u>Soils</u> Reclassified soils to unsuitable, very limited, somewhat limited & not limited <u>Flooding areas</u> Reclassified flooding zones to unsuitable & frequent, occasional & rare, & none <u>Erosion (slope)</u> Ranked slope into classes 0-5 (deg.) very good, 5-10 (deg.) good, 10-20 (deg.) limited, 20+ (deg.) unsuitable Used 'combine' to derive composite surface of all combinations of *soil-flood-slope* classes Reclassified the combinations into four suitability ranks
	Economic Value Block group data Census 2000 Summary File 3 – SF3 (housing units, vacancy data, and value of owner occupied housing units)	Census 2000	Block Groups: http://www.esri.com/data/ SF3 block group data: http://factfinder.census.gov/	<u>Popular sale areas</u> Calculated a ratio of vacant for sale housing units to total vacant housing units <u>High-priced neighborhoods</u> Averaged the property value of owner-occupied housing units Combined both layers into a normalized average

	Zoning / land use suitability: permits, easement proximity to utilities	2000 and later	Chelan & Douglas County Planning Departments Douglas: ftp://ftp.douglascountywa.net/	Generalized Douglas zoning layer Reclassified Chelan parcel data based on USGS land use classification codes Assessed the legislative suitability of the merged Chelan land use/zoning & Douglas zoning layers based on County Comprehensive Plans Ranks: 1 (lowest): agriculture, recreation, and barren land 2: rural resources, industrial, transportation 3: planned development, residential and mixed uses
	Combined the three derived rasters using the weighted summation aggregation function. Five weight vectors were considered {physical [p], economic [e], legislative [l]}: {0.3334,0.3333,0.3333}, {0.2,0.6,0.2}, {0.6,0.2,0.2}, {0.2,0.2,0.6}, {0.3,0.5,0.2} the resulting layers had a min correlation of r=0.76 with 99% significance except for the following pairs (1) 0.2[p], 0.6[e], 0.2[l] versus 0.6[p], 0.2[e], 0.2[l] (r=0.61, 99% significance); (2) 0.6[p], 0.2[e], 0.2[l] versus 0.2[p], 0.2[e], 0.6[l] (r=0.64, 99% significance). Since the 0.6[p], 0.2[e], 0.2[l], combination was present in both pairs, it was picked as the final layer. The 0.2[p], 0.2[e], 0.6[l] (legislative dominates) combination is the least reliable in terms of source data and therefore was removed from further analysis. Finally, the 0.2[p], 0.6[e], 0.2[l] (economy dominates) was dropped because the data is at very coarse scale (census block groups).			

Appendix B

This section outlines the procedure for calculating the net demand for land development extrapolated to the year 2025. The procedure was adapted from Barrett and Blair (1988). Data sources (accessed June 2007): www.ofm.wa.gov (housing unit and population data), http://www.realestateeconomics.com/ (building permit data), and http://seamless.usgs.gov/ (urban land use data).

Step	**Description**	**Value**
1	Housing to population ratio between 1990 and 2006	0.445
2	Population projection in 2025	57,862
3	Housing estimation in 2025: step 1 times step 2	25,749
4	Housing in 2000	17,353
5	Net housing demand in 2025: step 3 minus step 4	8,396
6	Urban area in 2000 (in 4 acre units)	9,300
7	Urban area per housing unit in 2000: step 6 divided by step 4	0.5359
8	Demand for urban area in 2025: step 5 times step 7	~4,500

Reference

Barrett, G.V., & Blair, J.P., (1988). *How to Conduct and Analyze Real Estate Market and Feasibility Studies*, 2nd Edition, Van Nostrand Reinhold, New York