Routledge Studies in Public Administration and Environmental Sustainability

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Climate change, loss of habitat and bio-diversity, water security, and the effects of new technologies are placing pressure at all levels of government for effective policy responses. Old policy solutions and the administrative processes associated with them not only seem inadequate for managing environmental and energy sustainability issues, but even counterproductive. The challenge for societies worldwide often is how best to harness in the public interest the dynamism of markets, the passion and commitment of nonprofit and nongovernmental organizations, and the public interest oriented expertise of career civil servants at all levels of government. *Routledge Studies on Public Administration and Environmental Sustainability* focuses on core public administration questions as they relate to the topics of environmental, energy, and natural resources policies, and which together comprise the field of environmental sustainability.

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10 All politics is spatial

Integrating an agent-based model with spatially explicit landscape data

Hal T. Nelson, Nicholas L. Cain, and Zining Yang

"All politics is local."

(O'Neill and Hymel[1])

Tip O'Neill's famous quote is a pithy way to introduce the topic of integrating real-world data into agent-based modeling research.[2] O'Neill's truism stresses that politicians have to know their constituents in order to win elections, and that these constituents are primarily concerned about local issues. For example, what matters to a person in Cambridge, Massachusetts, home to Harvard and MIT, often is very different from what matters to a resident in blue-collar south Boston, where up to 75% of households earn less than US$30,000 per year.

If one accepts the premise that local issues are defined in large measure by local institutions, demographics, and economic conditions—all of which vary from place to place—then the implication is that all politics is *spatial*. Seen this way, "local" is just a synonym for "spatial," and this is especially the case when it comes to issues of environmental justice (EJ), for which geospatial factors influence both the location of pollution and the "social geography" of demographics.[3] Another implication is that urban sustainability is inherently a spatial issue. Because of this, agent-based models (ABMs) designed to study EJ issues can benefit greatly by taking local spatial data into account.

Fortunately, as the previous chapters have noted, new approaches to simulation are now allowing the integration of real-world data with the rule-based logic of the computational environment. Integrating geospatial data generated by geographic information systems (GIS) with agent-based modeling techniques opens up new vistas for theoretical research and especially for applied analysis of use to practitioners. This is particularly the case when the interactions of agents in an ABM, and subsequent emergent behaviors, are conditioned by properties that vary by location. For the policy analyst or researcher, GIS-ABM models can improve the empirical validity of explanations and provide decision support to policymakers.

In this chapter, our first goal is to introduce basic theoretical considerations for fusing GIS data and ABMs. Next, we highlight the advantages of

coupling the approaches and examine some relevant software packages. We then present a spatially explicit multi-agent simulation, which we use to simulate two scenarios and make some inferences regarding EJ concerns over the siting of locally unwanted land use (LULU) facilities. We conclude with policy and research implications of our findings for urban sustainability.

Integrating agent-based modeling with GIS

To begin, we discuss key definitions and theoretical considerations for integrating spatial data and agent-based models. Spatial data models represent geographical phenomena either as discrete objects on a layer of data, or as continuous fields that form surfaces. In the discrete objects approach, houses may be represented as points, highways as lines, and Census tracts as polygons. These real-world features are defined by attributes, such as population density or landscape cover, and by location in a fashion that allows placement on a computer-generated map.[4]

In contrast, agents within an ABM may contain location information and various data attributes, but agent interactions, according to various rules, are the focus. ABMs are process oriented and dynamic in that they simulate the interactions of agents over time and have detailed scheduling mechanisms that guide agent behavior.[5] The focus of an ABM is often on emergent patterns that arise out of micro-level interactions (as is described in the earlier chapters). On the other hand, GIS models are data oriented and express the structure of entities in the real world in relation to each other.[6] GIS models usually employ a static temporal representation consisting of a spatial "snapshot" of the arrangement of objects at a given time. In summary, ABMs are *process oriented* and GIS models are *spatially oriented*.

Integrated ABM-GIS models can be categorized as "loose," "moderate," or "tight" according to how data and processing are shared across the models.[7] Loosely coupled models share files, often across separate software packages, asynchronously. In a loosely coupled model, it is often the case that GIS is used to prepare data for the ABM simulation, and then results are returned for visualization to the GIS. Moderately coupled models have the ability to remotely access and share database information across the modules. Tightly coupled models allow the GIS and ABM components to communicate with each other during the simulation run. Although tightly coupled models may run faster, they are usually more difficult to program.[8] Regardless of the degree of coupling, an integrated model requires careful consideration of its advantages and challenges, and of the relationships between model components.

Advantages and challenges

There are several theoretical and policy-relevant advantages—and also distinct challenges—that flow from integrating ABMs and GISs. The first advantage of integrated models is their ability to simulate distinct individuals and to model emergence. Emergence has been characterized as patterns arising from the *local* interactions of individual entities.[9] Being local, agent interactions are, at least partially, dependent on the spatial terrain.[10] Thus, in simulating emergent behavior, the built environment and natural features are often important factors—particularly in land-use planning and analysis of EJ issues. For instance, canyons and highways can inhibit or expedite the movement and interaction of agents and pollutants. Or, discontinuities in terrain and the built environment can lead to non-linear interactions that result in emergence. Since space in a GIS model is based on a geo-referenced coordinate system, an integrated model can model local interactions and "the effects of stochastic temporal and spatial variability," which in turn can be used to generate "phenomenologically realistic and complex behavior."[11]

The second advantage of integrating the two types of analytics is that real-world data allow rigorous validation of ABM results. Model verification and validation (as discussed earlier) is the process of evaluating whether the various components of the model behave as expected, and also whether the results of the model correspond to observed phenomena. In an ABM-GIS model, since simulation outputs are often presented in a geographic context, they can be compared to real-world outcomes and tested against real-world data.[12] Integrated ABM-GIS models can be validated against historical outcomes, demographic information, and other empirical data.

The final advantage of integrating GIS data with agent-based models is that ABM-GIS models can help decision makers optimize operational and resource allocation decisions.[13] ABM-GIS models can be constructed to create rigorous decision support systems (DSSs) which, in turn, can be used to analyze and plan projects and policies. DSSs allow users to simulate a range of possible policy inputs and outcomes, and can simulate the effects of a change in policy as compared to a business-as-usual path. A DSS can also be used for theoretical inquiry, as we demonstrate later in this chapter.

Our own experience with integrating agent-based modeling and GIS models has shown that it is not a trivial task—even though it may be crucial to working toward urban sustainability. Even with software that integrates the process and data models (as described below), considerable experience is needed in both agent-based modeling and GIS programming in order to get the integrated model to function properly. For example, modelers must clean and recode Census data so that the ABM software can process them. The map projection system used by the GIS model to translate location information needs to be recognized by the ABM software. Most importantly, procedures in the ABM code need to be carefully developed to account for the four relationships discussed below.

What to consider

In order to achieve the advantages discussed above, which can help practitioners improve local sustainability, agent-based and geographic models must be carefully integrated. Brown et al. identify four key relationships to consider:[14]

1. It is crucial to establish valid identity relationships between agents and GIS data. Agents representing citizens, for instance, can be instantiated in the ABM on a 1:1 or a 1:many basis. Representing the citizens in a Census tract with fewer agents in the ABM can help the model run faster, but may harm model validity, especially if agent behavior is conditioned on the frequency of agent interactions or their movements across tracts.
2. Model integration requires careful attention to causal relationships and feedback loops. Agent behaviors can affect spatial features and their attributes, which in turn can influence agent behavior. One example is readily familiar to EJ researchers: an increasing number of polluting firms move into an area, which results in a change in the zoning of a parcel from commercial to industrial (cf. Chapter 8). In this case, the results of the ABM (e.g., decisions by firms to move) must update the GIS data model (e.g., the zoning attributes for each tract), which, in turn, may influence future decisions made by agents in the model.
3. Once causal relationships have been specified, temporal relationships must also be delineated. Changes to agents and to the features of the GIS model need to occur within a realistic timeframe and be updated as simulation time progresses.
4. In integrated models, careful attention must be paid to spatial relationships and interactions between ABM and GIS components. Spatial data include the location of agents upon model initialization, the topography of the model space, and the geographic rules that govern how agents move. Model builders must consider how agent interactions translate into movement, how far and how fast agents move, and whether they can cross boundaries such as rivers or roads. Similarly, spatial rules might also require that houses cannot be built on top of existing houses, or agents cannot occupy the same place at the same time.

Once analysts have considered these four types of relationships and made efforts to plan their model, programming can begin using a growing range of computer-based environments.

Software platforms

The good news for the analyst who wishes to combine geographic information with agent-based simulation is that most ABM platforms have added at least basic spatial data capabilities. Given this, the most straightforward approach to model fusion is to include spatial data in one of the agent-based modeling platforms listed in Table 10.1, all of which are either open source or free.

Table 10.1 Select software applications and platforms for GIS-ABM analysis

ABM toolkit	*Description and URL*
NetLogo	NetLogo includes basic raster and vector GIS capabilities via a built-in extension; ccl.northwestern.edu/netlogo/docs/gis.html
MASON	The GeoMason extension adds advanced vector and raster capabilities to MASON; www.cs.gmu.edu/~eclab/projects/mason/extensions/geomason/
Repast	Some GIS is provided within Repast by the GeoTools extension and Java Topology Suite, and Repast can be linked with Esri ArcGIS via Agent Analyst; repast.sourceforge.net
Agent Analyst	Agent Analyst provides a powerful integration of Esri ArcGIS with Repast; resources.arcgis.com/en/help/agent-analyst/
R	The R statistical environment has basic spatial features, packages such as "sp" add power, and ABM capability can be added through the "RNetLogo" package; cran.r-project.org/web/views/Spatial.html
GAMA	A new, dedicated ABM-GIS platform; code.google.com/p/gama-platform/wiki/GAMA

Note: URLs provide links to additional information.

The software list in Table 10.1 is by no means comprehensive. Nikolai and Madey find over 50 different multi-agent modeling toolkits which range from open-source progenitors of agent-based modeling (such as Swarm), to commercial software (such as AnyLogic) that includes agent-based tools.[15] However, according to an analysis of research papers, the programs most frequently used by scholars in the past few years are NetLogo (used in previous chapters), Repast, Swarm, and MASON.[16] Given that Swarm is increasingly being supplanted by easier-to-use platforms such as Repast (which borrows many concepts from Swarm), we chose to highlight the applications presented in Table 10.1.

NetLogo is the first application we list because of its popularity and ease of use, and because it is used in previous chapters in this book. Given that the model we describe later in this chapter (the SEMPro DSS) was also authored in NetLogo, we discuss the capabilities of this platform in more detail below. Other ABM simulation platforms also include GIS capabilities, but require more complex programming. The MASON multi-agent simulation platform, for instance, provides very powerful capabilities, but must be programmed in Java. The MASON environment is broken into model-construction and visualization modules, and spatial data can be integrated using the GeoMason extension.[17] The Repast (aka the Recursive Porous Agent Simulation Toolkit) platform is another powerful multi-agent tool that can integrate spatial data. Although GIS data can be handled natively in Repast, more sophisticated capabilities are made available by using Agent

Analyst to integrate with Esri's ArcGIS suite of software.[18] R, an open-source statistical analysis platform, has the benefit of being able to run hundreds of different software modules. Available packages allow the addition of GIS capabilities within the R environment. Still other packages allow the integration of NetLogo within R or the use of R within NetLogo.[19]

NetLogo and spatial data

As described in Chapter 3, NetLogo has several advantages over other approaches: it is relatively simple to program and includes an intuitive, built-in user interface, giving it both ease of use and transparency in design. In addition, NetLogo imports GIS data using the now standard Esri "shapefile" format, or the Esri ASCII Grid file for raster data. The program can generate elements (such as agents representing people or firms) based on GIS data and can also generate variables based on the attributes of the spatial data.[20] To use these capabilities, spatial data must be created with a stand-alone GIS application or imported via an existing shapefile. After agents or patches are instantiated using the spatial data, agents within NetLogo can become spatially aware and thus interact with GIS data.

Although various attributes within the GIS data (e.g., population density) can be translated into elements within the NetLogo environment, more sophisticated kinds of geographic analysis are not yet supported. NetLogo is also limited in its ability to communicate with external datasets and cannot write back to shapefiles directly. However, it can update geographic information stored in the NetLogo program. Another drawback to using GIS data within NetLogo is that the GIS extension slows NetLogo's computational performance. Also potentially problematic is the small size of the graphical user interface (GUI) "window" available in NetLogo to view geographic data. These limits aside, NetLogo's ease of use makes it the go-to tool for many analysts, and programs such as ReLogo allow NetLogo code to be imported into more powerful environments such as Repast.

The fusion of agent-based simulation with spatial data is a rapidly evolving field. As this short introduction indicates, there are many different software applications and approaches to integration of ABMs and GISs. In the next section, we discuss the construction of the Sustainable Energy Modeling Program (SEMPro) and delve into the results of some simulation scenarios that analyze questions relevant to environmental justice and sustainability.

A case of a GIS-enhanced ABM for decision support

Power and environmental justice

As any student of politics will tell you, power matters. The SEMPro model allows us to simulate decision outcomes under different levels of citizen power. The model can represent a project in a *physical* geography (including physical constraints) while accounting for the *social* geography of power, and then simulate the impact of interest-group bargaining on regulatory decision making. Our results indicate that despite all the money spent on assessing the engineering aspects of major infrastructure projects, citizen participation and political power are more important to stakeholder bargaining outcomes than the level of local (physical) disruption that a project causes.

The SEMPro decision-support model presented here simulates the complexity of infrastructure siting by fusing: GIS data for a specific locale, with an agent-based model of citizen attitude and behavior diffusion, and spatial bargaining models of stakeholder and regulatory decision making. Users can simulate the geospatial, engineering, social, and political attributes of each project (as explained in more detail in Abdollahian et al.[21]). SEMPro can be characterized as a loosely coupled ABM-GIS integrated with game-theoretic stakeholder bargaining modules. Although the results are not returned to a GIS application, they are presented within a real-world spatial context using the ABM graphical interface.

Below, we briefly summarize the basic architecture of the current iteration of the SEMPro model, and then simulate two different scenarios with the goal of examining EJ issues. By gaining insight into the dynamics of siting decisions, including how citizens interact and stakeholders bargain, users of the SEMPro DSS can reduce sociopolitical conflict and integrate a wider range of stakeholder concerns into a LULU project's design. DSSs like SEMPro allow users to improve planning outcomes by simulating tradeoffs and alternatives.[22] These capacities are key to sustainability, for the sustainable future will still require LULUs within or near urban environments.

The SEMPro model

Agents and their decision-making modules

The Sustainable Energy Modeling Program is a decision-support software program specifically designed for energy facilities siting, but which can be used for almost any large-scale project useful for sustainable cities. The software simulates how competing interests, and community and project attributes, shape siting outcomes. The citizen agents, stakeholders, and regulators in the model are all trying to maximize their own utilities, given the assumption of bounded rationality. SEMPro has three sequential sub-modules that run for up to 25 time steps, with each time step representing 2 months of calendar time. Figure 10.1 depicts the overall model architecture and details key module processes.

Citizens react to infrastructure siting projects by forming opinions, interacting with their neighbors, multiplying their power by forming community-based organizations (CBOs), and engaging in extra-process legal or political

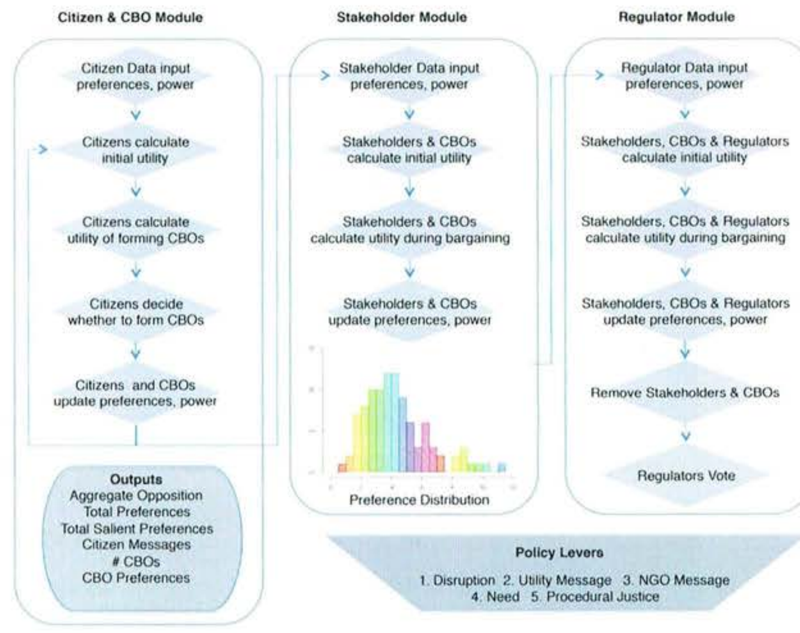

Figure 10.1 SEMPro model architecture
(Abdollahian et al. 2013, used by permission)

activities.[23] In the first module of SEMPro (the Citizen & CBO Module), GIS-based data on the project size and route, on land use, and on the location of residents informs agent-based simulations of individual interactions. Figure 10.1 shows how these behaviors can result in the formation of CBOs that either support or oppose such projects. (CBOs are shown in the bottom part of Figure 10.2 as red (opposed) or blue (supportive) "faces.") Because citizens are typically opposed to the project, pro-development CBOs are uncommon and, if they do appear, not very influential because they have few members. As citizens interact to support or oppose the project, new agents representing citizen-based organizations may appear in the neighborhood.

The second module of SEMPro, shown in the center column of Figure 10.1, focuses on bargaining between CBOs and other organized stakeholders. In this context, "stakeholders" are non-CBO interest groups and government agencies that have the potential to influence the siting process. In the siting of energy projects, there are usually at least a dozen stakeholders that can include local, state and federal agencies, environmental organizations and other user groups, and utilities and power producers.[24]

Stakeholders seek to influence citizen opinions and emergent CBOs, and also other stakeholders, in order to maximize their organizational interests. (These stakeholders are shown in the circle in the top-right section of the

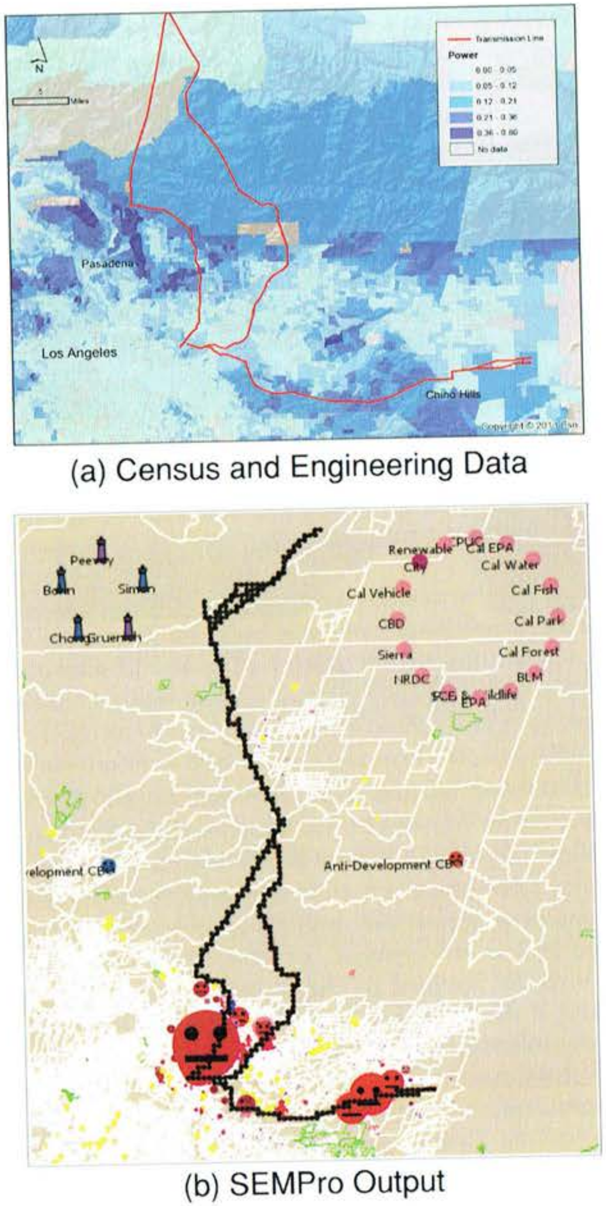

Figure 10.2 Study area and SEMPro output

Note: Top panel shows the route of the Tehachapi Renewable Transmission Project (TRTP) transmission line, superimposed on the relative power of Census block groups, as it runs through Los Angeles and San Bernardino counties. Citizen power is the product of average household income and average household education. The bottom panel shows a similar area as seen through the "windshield" of the SEMPro ABM-GIS model, with CBOs depicted as either red (opposed) or blue faces. One portion of this figure, from Abdollahian, Yang and Nelson (2013), is used by permission.

bottom panel of Figure 10.2.) Preference data for stakeholders come from a web-based survey administered between July 2011 and March 2013.[25] The use of such stakeholder information is not standard in GIS or ABM, but shows another way in which an ABM can be enriched by real-world information. In the model, stakeholder bargaining incorporates non-cooperative game theory to reflect competing interests during the process.

The final module of SEMPro, shown in the far-right column of Figure 10.1, simulates the regulatory decision-making process, which is based on the interplay between CBOs (representing the public), stakeholders, and regulators. This module makes use of the same non-cooperative bargaining theory as the previous module. Regulators participate in the stakeholder bargaining process during time-steps 16–20. After time-step 20, regulators bargain among themselves and decide the project's fate using a majority-voting rule. (Regulators and their preferences are represented as chess pieces in Figure 10.2 in the upper left-hand side of the bottom panel.)

GIS data in SEMPro

As discussed above, GIS data are critical for representing the real-world attributes of the project in the decision support system. As described in the next paragraphs, spatial data used in the SEMPro model include project route and size, topographical data, and US Census data.

Data on project route and size can take the form of lines or polygons (representing power lines) or points (representing power plants or waste incinerators). By overlaying GIS project data onto US Census data, the project then follows, or is placed into, the real-life attributes of the community. The top panel in Figure 10.2 shows the transmission line route for the SEMPro case study, as well as the varying levels of citizen power in the area. With greater resolution, Figure 10.2 would reveal that the transmission line mostly follows existing rights of way through the region. These rights of way constitute the setback between the project and the houses along the route. The proximity of the citizen agents to the project is a key driver of attitudes to the project. We assume that the importance (salience) of the project to citizens is relative to the inverse of its distance. Less proximate citizens are less likely to get involved in the siting process because it is not as important to them.

We have also included gridded, topographical data into the model that represents the "viewshed," or the region where an agent could view the 200 foot-tall transmission towers analyzed in this particular instance. The current version of the model takes a simple approach based only on proximity, but future versions could integrate a more sophisticated use of topographic data.

US Census block-group-level data on population density are used to locate citizen agents in the ABM. Citizen agents are instantiated in the model at a rate consistent with US Census data and with one agent representing 1,000 people. GIS-based Census data on education and income, by block group, are also included as attributes of the citizen agents. Higher levels of income and education imbue citizens with greater political power, and more powerful citizens, because they have a stronger sense of self-efficacy as well as more resources and access, are more influential in affecting project outcomes.[26]

After the geographic information summarized above is input into the model, different parameters and policy "levers" can be adjusted. One of the primary policy levers simulated in the model is the level of *disruption* that the project imposes on the community. Disruption is the cumulative effect of negative externalities such as aesthetic impact, risk of exposure to electric and magnetic fields, and reduction in residential property values. For transmission lines, disruption is measured as the height of the transmission tower, with 0 indicating no change to the existing landscape, and 1 indicating the maximum above-ground disruption of a 200-foot pylon. Smaller transmission towers are measured as values between 0 and 1 (e.g., 0.6).

Need is the perceived project need. The highest value for need is when the project has been approved by the state transmission operator and it improves reliability for the communities affected by the power line. Need is lowest when the power line carries power to other regions without significant local benefits. Need is assessed by subject-matter experts based on public statements from the project proponent and the independent system operator.

Procedure is an indicator of procedural justice, or to what extent the citizens think their preferences will be included in regulatory decision making. Gross has shown that the level of trust residents have in the decision-making procedure is critical to sentiment regarding a project—a reason why sustainability is assisted by trust between citizens, including minority citizens, and government.[27] Although this can be difficult to control in practice, work by Beierle and Cayford has shown that how policymakers shape public participation and integrate public comment can have a substantial effect on citizen sentiment.[28]

Utility message represents the number of pro-development messages the project sponsor sends to citizens to shape public attitudes. *NGO message* represents the number of anti-development outreach messages that nongovernmental organizations (NGOs) send.

One important parameter that is a constant rather than a policy lever is *talk-span*, which is the distance or neighborhood within which agents talk to each other and make decisions on whether to form CBOs.

Simulation study area

SEMPro was initially designed to simulate the siting of high-voltage transmission lines (HVTL). The Tehachapi Renewable Transmission Project (TRTP), located in southern California, was the case used for model construction. TRTP is a 173 mile-long HVTL project being constructed to connect wind generators in the Tehachapi-Mojave Wind Resource Area with customers located in the Los Angeles metropolitan area. By using

extra-urban area wind sources to provide power in Los Angeles, it should enhance urban sustainability, but the project has not been popular. Our model correctly highlights the opposition to Segment 8A of the project, which runs through the City of Chino Hills, located in the southwest corner of San Bernardino County.

The top of Figure 10.2 shows "political power" data for the study region. We calculate citizen political power by multiplying average household income by average education level and normalizing the data. As shown in Figure 10.2, darker colors represent higher levels of education and income. The bottom panel of Figure 10.2 shows the model's predictions for the spatial location of citizen messages in high-population-density Census block groups.

As one element of its validation, the model's predictions were compared with actual public comments. The SEMPro model's predictions match the comments submitted by residents of Chino Hills, and slightly over-predict comments from the Pasadena area (another city in the region).[29] Other model validation efforts included comparing the modeling outcomes with *a priori* theoretical expectations.[30]

Adding an EJ component

Given this model design and the validity tests performed, we now describe scenarios of interest to environmental justice researchers and sustainability practitioners. Although the SEMPro model was not explicitly designed for EJ analysis, we can use it for this purpose by simulating outcomes under two different scenarios. In the reference-case scenario, the power of agents varies according to Census-derived data as shown in the top panel of Figure 10.2 and described above. We contrast this with an egalitarian case scenario, where all agents have the same (maximum) level of power. In this case (not shown), a power map of the region would be entirely dark blue.

Since the model's algorithms dictate that more powerful citizens are more influential (because they are more likely to send messages to regulators and more likely to form CBOs), in the reference case we expect fewer citizen comments and less advocacy, as many citizens have less than full power. In contrast, in the egalitarian world scenario, we expect that more messages will be sent and more CBOs will form as all citizens have a high level of power. Thus, comparing the reference (GIS-based) scenario to an egalitarian scenario allows us to consider what outcomes would look like in the *absence* of environmental *in*justice.

Model outcomes

We conducted a quasi-global sensitivity analysis by varying all input parameters across their entire range in three steps (minimum, mean, maximum), which resulted in 729 runs for each of the two scenarios, or a total of 1,458 runs. Each run contained up to 25 time steps for a total of 29,154 observations. The simulation results were pooled together and ordinary least squares (OLS) estimation was used to create standardized β (beta) coefficients for input parameter comparability and model performance.[31]

In Table 10.2, Model 1 shows the impact of input parameters on citizen opposition to the project, which in turn drives formation of CBOs and thus influences regulators in the subsequent modules, as shown in Figure 10.1. The dependent variable is the result of the interaction of the total number of citizen messages and the median preferences of citizen agents. This captures *both* the direction and intensity of public sentiment at the level of the study

Table 10.2 Pooled OLS estimations of citizen, CBO, and stakeholder preferences

	Model 1	*Model 2*	*Model 3*	*Model 4*
	Citizen preferences (opposition)	*CBO preferences*	*Stakeholder preferences*	*Citizen preferences*
Disruption	0.113***	0.001	-0.002	0.146***
	(0.000)	(0.506)	(0.333)	(0.000)
Talk-span	0.609***	0.904***	0.898***	0.609***
	(0.000)	(0.000)	(0.000)	(0.000)
NGO message	0.024***	0.008***	0.004*	0.024***
	(0.000)	(0.000)	(0.028)	(0.000)
Utility message	0.013***	0.003	0.002	0.013***
	(0.000)	(0.211)	(0.313)	(0.000)
Need	-0.015***	-0.007***	-0.008***	-0.015***
	(0.000)	(0.001)	(0.000)	(0.000)
Procedure	0.015***	0.002	-0.001	0.015***
	(0.000)	(0.428)	(0.689)	(0.000)
Power diff.	-0.125***	0.001	-0.004*	-0.077***
	(0.000)	(0.509)	(0.039)	(0.000)
Time step	0.632***	0.251***	0.296***	0.632***
	(0.000)	(0.000)	(0.000)	(0.000)
Power diff. * disruption				-0.067*** (0.000)
N	29,154	29,154	29,154	29,154
Prob > F	0.000	0.000	0.000	0.000
Adj. R^2	0.800	0.880	0.895	0.801

Note: Standardized beta coefficients; p-values in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. The dependent variable for Model 1 is a measure of citizen opposition.

area. Models 2 and 3 measure the impact of the drivers on dependent variables that are created within each module of SEMPro. The dependent variable of Model 2 measures CBO preferences and the dependent variable of Model 3 measures stakeholder preferences in a similar fashion.

As shown in the first column of Table 10.2, all Model 1 drivers are statistically significant and all of the signs are in the expected direction (with the exception of procedural justice). Community attributes and other control variables have a large impact on citizen advocacy and activism. First, the value of *talk-span* (β = 0.61) in Model 1 suggests that citizens communicate their opinions to regulators more frequently in well-connected communities. The implications of this finding are discussed in more detail below. As expected, each model time step, which represents 2 months of calendar time (β = 0.63), has a positive and significant impact on the number of citizen messages. Given the structure of the SEMPro model, we expect a high Adjusted-R^2, which we can see with Model 1 at 80%.

The level of disruption has the most substantial effects among the policy levers in the SEMPro model. Given the value (β = 0.113), we can say that an increase of one standard deviation in the level of project disruption results in a 0.11 standard deviation increase in negative citizen response. Looking at the other policy levers, although effect sizes are small, both NGO messages and utility messages increase citizen opposition. The relationship of utility messages to citizen opposition is counterintuitive but logical. The harder utilities "push" citizens, the more citizens push back.[32] The impact of project *need* in Model 1 is negative (β = -0.015), which is consistent with existing theory that when a project is perceived as necessary, it will generate less opposition. Perceptions of procedural justice have a positive effect (β = 0.015), which suggests that citizens who view the process as fair are more likely to participate by expressing opposition. This finding is counter to theoretical expectations and previous research, and requires further investigation.[33]

Looking at the results for *power diff.*, we can gain some insight into the differences between the EJ scenarios. Recall that we have 729 simulations for the reference case with power levels calculated from US Census data, and the same number of simulations with all citizens having maximum power. In the regression models, *power diff.* is a dummy variable, with 0 for the EJ simulations and 1 for the reference-case simulations. The negative coefficient for *power diff.* indicates that in the reference-case scenario where power levels vary based on Census data, fewer messages are sent to regulators. This implies that in an egalitarian siting process more citizens would participate. The effect of power is strong: the standardized coefficient for power differential is larger than the coefficient for disruption, one of the primary drivers of opposition.

In Model 2, the coefficient for *power diff.* indicates that varying levels of citizen power have no significant effects on CBO preferences. Variation in citizen power impacts CBO influence in the siting process (as more powerful citizens are more likely to create CBOs and more CBOs are more effective), but in our simulations has no significant impact on CBO preferences. Turning to Model 3, the *power diff.* coefficient indicates a very small (β = -0.004) and significant ($p<0.05$) effect on stakeholder preferences. In other words, we can expect slightly more opposition in a more egalitarian world. Since power differentials do not directly affect CBO preferences in the model, the unequal distribution of citizen power affects stakeholders through other channels.

Finally, in Model 4, we interact two of the most important variables from an EJ perspective, disruption and power differential, and then assess their effects on citizen messages. The negative interaction coefficient indicates that variation in citizen power in the reference case reduces the effect of disruption on the number of citizen opposition messages sent to regulators. The interaction term predicts that, holding all other variables constant, reduced equality of citizens reduces the effect of disruption on messages sent to regulators. *Ceteris paribus*, we can predict that proponents of very disruptive projects are more likely to get their projects approved in areas where citizens have lower levels of income and education.

Discussion

Our simulation analysis in this chapter finds that low levels of individual income and education reduce public participation in energy facility siting. Less powerful individuals are less influential in influencing project outcomes. The findings of the effects of power differentials are not surprising as they are coded into the SEMPro model structure. What is surprising is the relatively large effect size of power inequality. The standardized coefficient for power inequality is larger than that of project disruption, holding other variables constant.

Our findings may be of use to several debates in EJ research and practice, and thus have relevance to our pursuit of sustainable cities. First, we find support for sociopolitical explanations that argue that poor and/or uneducated communities have more difficulty developing effective opposition to disruptive projects.[34] A second implication relates to the temporal debate about which came first: locally unwanted land uses, or poor and minority communities. While not explicitly a panel analysis, our ABM results are consistent with research that finds that unwanted facilities are imposed on existing communities with a low ability to oppose them.[35] This is consistent with the infamous Cerrell Associates report of 1984, which recommended that new waste incineration facilities be sited in poor communities.[36]

The results from the interaction between disruption and power also show that the inability of less powerful communities to participate in siting decisions attenuates the negative effects of a project's disruption on planning processes. This supports research showing that project sponsors are aware of the relative ease of siting projects in less powerful communities and that this has guided siting decisions.[37] The implication is that while low-disruption projects may be sited through high-education and high-income communities, high-disruption projects are more likely to go through less powerful communities. More egalitarian residential power relationships, or siting processes that treat groups in a more egalitarian manner, would mean that very disruptive projects would face higher levels of opposition. This is troubling for practitioners who seek to develop more sustainable cities since, in this case, there is a tradeoff between siting an environmentally beneficial project and imposing its costs on the poorer and less well educated.

We also find some methodological implications from our simulation and analysis. Some EJ research has treated hazardous waste facilities and other environmentally harmful projects as dichotomous units where the facilities either exist or do not exist.[38] However, this coding could actually be understating the effects of race- and class-based biases on facility siting. For example, if small facilities with few toxic emissions sited in wealthy communities are coded the same as larger, high-emissions facilities sited in poorer, more diverse neighborhoods, then multivariate regression will underestimate the impact of race and income on pollution exposure. Our model represents the size of the project (measured as a variable taking on values between 0 and 1), as well as agent proximity to the project, as continuous variables within a specific physical context. As we detail above, this provides greater precision in measuring disruption and understanding the impact of geography on agent decisions—key issues for decision makers. We suggest improving measurement of disruption whenever possible. This research recommendation is consistent with social epidemiology methodologies that use GIS and facility-level emissions data to estimate individual health impacts across spatial scales.[39]

There are also several policy implications from the findings of our ABM-GIS model. The first policy implication is that a more egalitarian process for siting infrastructure would result in more citizen opposition, fewer highly disruptive projects near citizens and, possibly, greater social justice in the long run. Our findings support the importance of institutionalized public participation, which tends to increase communication and ensure stakeholders are representing community sentiment.[40] A more egalitarian planning process could proactively survey all the citizens impacted by a project, rather than employing the passive notification and comment period approach, which tends to favor wealthier and more educated individuals. Such an approach could enhance sustainability in more than one way, by increasing the justice of LULU placements, and also enhancing government-citizen trust.

The second policy implication is that ABM-GIS models can be an effective way to integrate social justice issues into planning for specific projects. Siting issues are quite complex, and decision makers must balance competing concerns while following a highly institutionalized process. The California Environmental Protection Agency has created a web-based GIS tool showing the communities in California with the highest burden of pollution from a variety of sources.[41] Adding the ability to simulate the manipulation of policy levers, such as disruption or project location, could result in better understanding of the costs and benefits of different project scenarios, which in turn can reduce conflict and delays, lower project costs, and allow more successful implementation of sustainability-supporting projects such as TRTP.

Using the SEMPro DSS to simulate EJ issues as is done herein is not without limitations. The current version of the SEMPro DSS only includes parameters for the simulation of class-based EJ outcomes, and does not include Census data on race and ethnicity. Since it has been shown that minorities often also have less education and income, our findings could be generalizable to these demographics—but earlier chapters indicate there is something particular about being in the minority.[42] Given the findings of Chapter 6, which show that minorities may cluster near amenities as well as disamenities, there is room for further study of how race, education, and income influence infrastructure siting. Nonetheless, the case illustrates the use of an ABM-GIS, and these considerations suggest how policy analysts and planners, researchers, and practitioners can develop models that are appropriate to their own locales and issues.

This chapter has presented some core concepts, issues, and platforms for integrating agent-based models with spatially explicit GIS data. After discussing some of the advantages and challenges associated with ABM-GIS, we have described the design of the SEMPro DSS and shown how it can provide insight into questions of relevance to the EJ community—and, in turn, to sustainable cities.

The integration of these two technologies can yield substantial benefits to researchers, and to policymakers and practitioners. For the research community and concerned practitioners, use of the ABM-GIS SEMPro provides support for the theory that hazardous facilities are imposed on communities that lack as much power to resist them. Methodologically, our simulations also provide support for the importance of analyzing externalities using continuous (rather than discrete) variables in a geographic context.

Future research could also analyze siting cases for which the scale of the disruption of harmful projects was reduced at the design phase and compare these to projects that were approved without modifications. The predictors of this outcome variable could then be investigated for biases in race and class, which could provide evidence regarding the proposition that more powerful communities are able to reduce project impacts more successfully than less powerful communities.

For practitioners who want to integrate EJ concerns into existing frameworks, spatial DSS and ABM-GIS platforms show considerable promise. At the beginning of this chapter we posited that "all politics is spatial." While this may be a slight exaggeration, the theory and empirics presented here show strong support for the conclusion that spatial heterogeneity is an important factor in siting outcomes. In other words, what matters to individuals varies by physical location, as well as by other factors such as income. Therefore, integrating GIS data into environmental justice and

sustainability research and simulation is critical to modeling, analyzing, and addressing these issues in specific locales.

In our simulations, individual-level attributes, such as income and education, have effects of a magnitude similar to that of the level of disruption caused by a project. We also find that the effect of the project's disruption on the number of citizen messages is dependent on citizen attributes that vary geographically. All of these factors stress the value of coupling agent-based modeling with GIS data for local policy and planning. As any student of politics will tell you, power matters. Despite all the money spent on assessing the engineering aspects of siting projects, citizen power and participation are more important to stakeholder bargaining outcomes than project disruption—the physical nature of the project—in our modeling. Our research highlights how the spatial attributes of power can be integrated with agent-based simulation to provide actionable insights for policymakers, researchers, and citizens.

Notes

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