System-of-Systems Approach to Modeling Residential Burglary Patterns and Crime Prevention

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A B S T R A C T

Crime modeling is challenged with capturing human behavior and decision making processes in the context of evolving urban environments. Better understanding of criminal drivers, responses to law enforcement and social interrupters are needed to assist policy-makers in improving criminal deterrent and intervention strategies. With this motivation in mind, a system-of-systems model has been developed to study residential burglary and law enforcement effectiveness in the West-central districts of Tucson, Arizona. To analyze human behavior influenced by system-level attributes, a method for performing agent-based modeling within a realistic social and geographic environment has been employed. While similar efforts have focused on modeling aggregate criminal behavior and deterrents in isolation, this effort considers a unique perspective to study citywide dynamics and gain insight on localized emergent phenomenon. Two cases were analyzed to demonstrate model efficacy. Burglar activity was monitored in response to a large road construction project and redistribution of police patrol routes based on criminal migration. Initial results demonstrate promise in anticipating gaps in government policy, police structure, and other social constructs related to residential burglary and crime prevention.

1. System-of Systems Perspective Overview

This effort couples a geographic city representation with an agent-based burglary and crime prevention model. The unique coupling permits study of endogenous city-wide factors on burglar events and law enforcement response. Tucson, Arizona was selected as the subject city, chosen for its grid-like road structure, varied landscape and diverse population. To ensure a comprehensive socio-economic crime model, a system-of-systems (SoS) approach was employed. [1] Given the operational and managerial independence of city subsystems working toward the common goal of prosperity, Tucson was studied as an acknowledged SoS. No one organization or person controls law enforcement, lawmakers, or citizens to all ends. Each function independently, following policies and operational guidelines established by local and state governments.

The SoS problem formulation calls for a discrete hierarchical modeling approach. As an example, Tucson is comprised of geographically distributed communities, all linked via a grid-based network of public and private transportation routes. Specific localities are operationally and managerially independent, with separate local governments, education districts, police jurisdictions, sources of funding and even differing regulations. In addition, Tucson contains a diverse population which varies between neighboring communities and even at the individual street level. Accurately capturing all constituent elements requires careful attention to system-level interactions and potential feedbacks.

Adopting the lexicon in [1], Table 1 describes the SoS structure. The matrix organizes features of Tucson into four distinct categories (resources, operations, policies and economics). Several layers of abstraction (denoted α, β and γ) exist for each category, where the α-layer corresponds to a micro-level view of the SoS containing the smallest discernable system elements, and the γ-layer corresponds to a macro-view for each SoS category. The communication and interaction of constituent SoS entities across trans-domain categories defines the primary model dynamics. Rather than capture all constituent SoS variables and interactions in a monolithic simulation, critical low level resources, operations, economics and policies highlighted in Table 1 were emphasized.

Table 1
System-of-Systems Lexicon for an Urban Environment

Level	Resources	Operations	Economics	Policies
γ	City wide crime management resources	City council redevelopment planning, Redistricting	Tax re-distribution	City council policies
β	Schools districts, Community properties, Police stations, Public parks Recreation centers, City taxes, Prisons, Crime rings	Neighborhood watch programs, After-school programs, Park restoration efforts, Police communication networks	HOA fees, School district levies, Police funding, Wealth	Police jurisdictions, Community regulations, Prison capacities
α	Police, Buildings, Citizens, Roads, Transportation, Local security measures, Surveillance equipment, Household income, Burglars	Daily activities, Work/social schedule, Police patrols, Home monitoring, Road closures	Person-to-person transactions, Individual home value, Income	HOA policies, Police policies, Span of crime from homes of offenders, Criminal heuristics

2. Agent-Based Modeling Approach

Modeling was performed within the Repast Simphony 2.0 suite [2], and leveraged the Repast City plug-in [3]. The plug-in provided baseline agent intelligence to follow roads, and calculate shortest routes to various destinations. The city layout was obtained from a geographic information system (GIS) database, containing roads describing network connectivity and land parcels representing buildings [1]. Additional data portraying general city demographics was incorporated as parcel attributes.

To justify the ABM approach, cities exhibit emergent behavior where aggregate crime and police statistics alone are insufficient to predict real-world dynamics. At the local level, burglary is an individual phenomenon, where burglars target specific homes based on individual property attributes, human reasoning and decision processes [4]. Closely linked to emergence is the ability of an ABM to create a natural description of a system under observation [5]. Juxtaposed with dynamic systems modeling which can offer a holistic view of aggregate crime using feedback structures [6, 7], ABM can capture spatially and temporally resolved crime events. ABM not only predicts general system reactions to input events but also provides insight as to how and where responses vary within a system. Integrating an ABM and geographic dataset enables predictions that demonstrate the impact of city layout, infrastructure and evolving human behaviors on burglary.

To simplify the ambitious task of modeling human behavior, this research focuses exclusively on burglaries driven by financial desperation and enabled by high opportunity. The simulation allows criminals to make circumstantial decisions, based on impersonal surface-level observations of their surrounding environment in concert with metrics describing their internal state. There were no attempts to model morality or personal relationships directly. Morality was assumed constant across all agents, providing a controlled environment to study system effects on crime. This approach circumvented hard-coding preconceived criminal dispositions into the model and mitigated the possibility of generating politically-charged or self-confirmed results. Although all criminals were assigned homogeneous personalities, they were subjected to different initial circumstances and varying distribution of resources.

[1] Parcel data was used in the absence of a comprehensive building layer for Tucson.

3. Modeling the SoS

The SoS model was comprised of a virtual environment and two agent classes representing criminals and law enforcement as portrayed in Figure 1. The virtual environment consisted of a building layer, community layer and transportation network. Behavior models were constructed for both criminals and law enforcement, allowing agents to interact with their environment and other agents indirectly. Given the SoS model structure, complexity is apparent and stems from the number of interacting, semi-autonomous agents, uncertain system boundaries, adaptive agent behaviors, emergence, and non-deterministic problem nature.

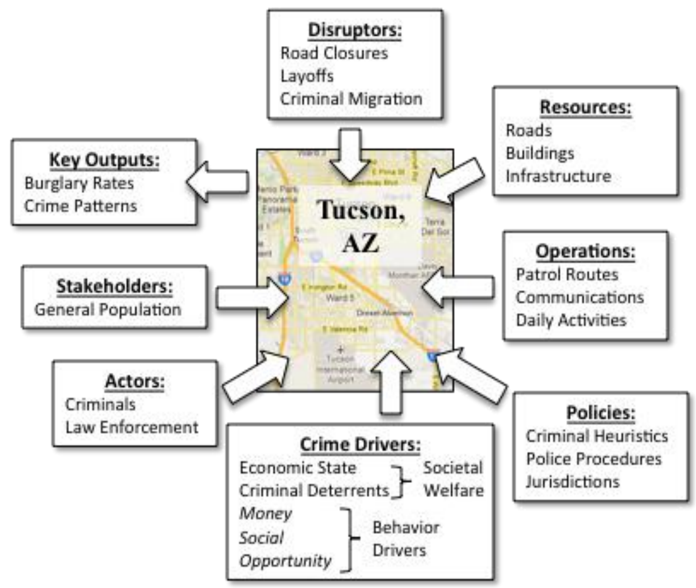

Fig. 1: Abstraction of Tucson SoS

3.1 *The Virtual Environment*

Fig. 2 identifies the SoS model geographic boundaries. The region includes the University of Arizona, downtown metropolitan center, Southwestern industrial park near interstate I-10, and upscale Sam Hughes suburb. This area comprises approximately 20% of greater Tucson and captures a variety of demographics, including a student population, higher and lower-income neighborhoods, an industrial district, numerous parks and downtown center. Data used to construct the region was obtained from the Tucson GIS Services Division repository, which is home to various independent shapefiles containing city infrastructure and census data. Rigid system boundaries were imposed to restrict the model to a feasible computational domain. In reality, the city acts as an open system allowing interactions with bordering communities.

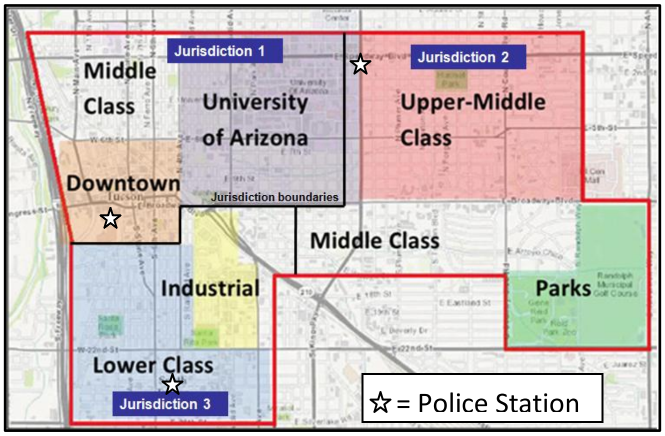

Fig. 2: Central Tucson, Arizona Economic, Social, and Commercial Sectors

3.1.1 *Building Layer*

Census data of Tucson was used to initialize buildings with varying attributes using information such as registered building type (residential, commercial, industrial and social), residential house values, and unemployment rates. The probability that residential buildings were assigned a security system was based on house values. More expensive houses, which are attractive to burglars, are also more prone to be secure. Further, given that a house had a security system, the conditional probability of the system being active was 50% [8].

Census based unemployment rates were used to initialize the probability that a given house was occupied, influencing the probability that a burglar would attempt to burgle the house. The three levels of residential occupancy are (1) unemployed (assumed 90% occupied throughout the day), (2) employed (assumed 25% occupied), and (3) vacant (0% occupied). Uncertainty exists in the assignment of property values, security, and occupancy levels to specific residences. This risk was mitigated by using aggregate census data at the tract level and distributing building attributes based on known statistics. This approach was considered sufficient to achieve the modeling goals established.

3.1.2 *Community Layer*

Just as each building was initialized with individual statistics, buildings within different β-level communities were initialized with census data attributes relative to specific areas, including occupancy and home value. The Tucson GIS Services Division provides shapefiles [9] describing the stress level in different Tuscon communities. Of the 27 factors that contribute to the stress level of a community, some include poverty rates, population density at various age levels, education levels, housing costs which are contributors to the propensity to burgle [10]. Different communities within the building layer are also assigned to different law enforcement jurisdictions based on Tucson patrol jurisdiction maps available through the GIS Services Division. Three distinct regions are patrolled by law enforcement, each with its own police station (see Fig. 2).

3.1.3 *Transportation Network*

The road connectivity layer served as a realistic network topology, constraining agent movements to specific pathways while navigating the city. In the case of city road structure, the road network served as an undirected network between destinations. The concept of major and minor roads was implemented, where weights were placed on each road, or network edge, such that agents determined the shortest path using Dijkstra's algorithm. The intersections of major roads served as nodes with high betweenness centrality. Due to the grid-like structure of Tucson, there were many connected nodes of degree four, and few intersections of higher degree. For this reason, the system has a very high nearest neighbor assortativity, meaning many nodes of the same degree are connected. Without the inclusion of road weighting, a large number of equally short paths between two points can exist, and the closure of any single road would have very little effect on the system. Therefore, weighting drastically affects agent movement, and effects the detrimentality of road closures. From an SoS perspective, these weightings ultimately determine the visibility of houses and their susceptibility to burglary, playing a key role in the system's dynamics.

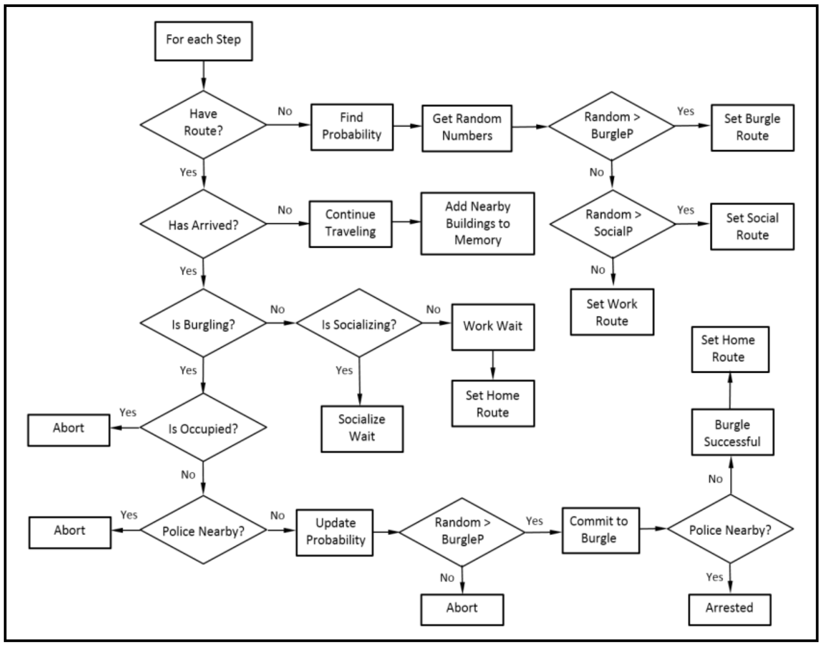

Fig. 3: Burglar Decision Model Flowchart

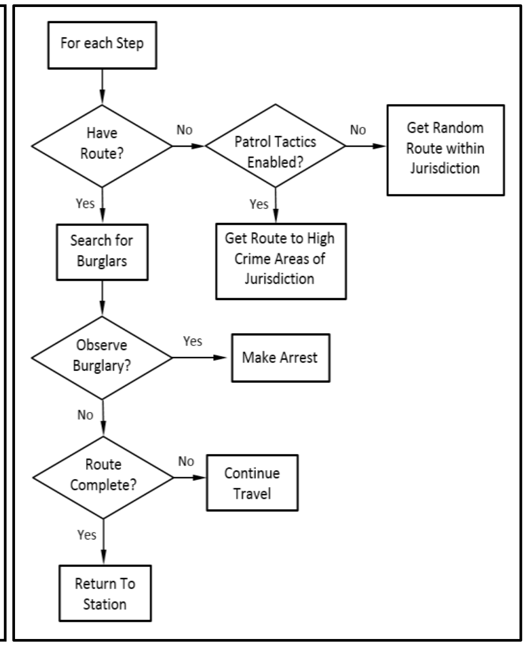

Fig. 4: Police Decision Model Flowchart

3.2 Agent Behavior Models

3.2.1 Burglar Model

The burglar decision model consisted of three decisively broad variables to describe internal state as demonstrated in the Appendix. The approach was similar to the PECS framework, which captures physical, emotional, cognitive and social factors [11]. Money, social need, and opportunity for crime were deemed the simplest reduction of internal drivers relevant to committing a burglary. Money comprises all personal assets, social need measures emotional state, and opportunity quantifies an agent's perceived ability to steal without being caught. It is not possible to numerically quantify these variables, since they are relative to personal disposition and outlook. Therefore, all three were measured on a scale from zero to one, with zero being low, and one considered high. The combination of these along with subsequent random draws were used to determine agent actions. Possible actions included going to work, socializing, travelling home, or committing a burglary.

Agent decisions were not triggered by a specific threshold or variable in the model. The coupled values of all three internal variables affected the probability of an action occurring. This introduced stochastic behavior that followed user-defined probabilistic trends, rather than programming discrete thresholds to drive decisions. There was no default money or opportunity level that caused an agent to burgle, allowing possible deviations in behavior between two agents with identical internal values. Agents were constructed to be self-regulating systems with actions acting as negative feedback loops, therefore causing the agent's internal variables to self-correct. Having low money caused agents to be more likely to pursue actions leading to increased wealth and vice-versa. For example, an agent with little money was considerably more likely to either go to work, or burgle, to increase wealth. An agent with considerable wealth was most likely to socialize, rather than work or burgle.

Figure 3 depicts the internal process used by criminals to navigate the map each time step. An agent without a current destination used the decision making process already described to select an action and subsequent route. After determining an objective, agents traversed the map committing nearby houses to memory. During the burgle action, a familiar house from memory was selected as the burgle target. En route to the target destination, an agent's internal states continued to change allowing them to reassess their action prior to burgling. Reassessment was based on perceived occupancy and presence of law enforcement.

3.2.2 Police Model

Police agents were modeled similar to burglars, but with a simplified decision making process and fewer actions. Actions included patrolling within a jurisdiction and returning to an assigned police station. Individual officers were not conflicted with competing needs, and by default would patrol as their baseline behavior.

Police passively interacted with burglars via the burglar's opportunity level. A burglar's perceived crime opportunity was significantly reduced after encountering an officer, effectively reducing their probability of burgling. The two systems actively engaged when a police agent encountered a burglar in the act of robbing a house. Fig.

4 defines the behavior patterns and logic implemented for police.

3.3 Model Assumptions

Many assumptions and trends were used to initialize and later validate features of the model. A best attempt was made to base assumptions on criminal heuristics provided by documented interviews with past convicted burglars, and crime statistics, obtained either locally for Tucson AZ, or at the national level. The following list contains those assumptions along with justifications.

- 17% of residences in the United States have security systems, of which 50% are actively used [8]
- Homes are targeted based on occupancy, accessibility, visibility, potential value, security, and familiarity [12]
- Nearly 50% of all burglars live within 2 miles of the homes they burgle [8]
- Burglary and poverty are correlated [10]
- Homes previously burgled or near recently burgled properties are at greater risk for burglary [12]
- As of the 2011 census, Tucson has a population of 525,796 citizens [13]
- Greater Tucson contains 940 sworn officers, which comprise roughly 0.2% of the total population [14]
- Based on geographical size, 20% of the police force are assumed stationed in the region modeled
- 65% of sworn officers are uniformed personnel, responsible for general patrol and crime response [15]
- With three work shifts, roughly 33% of uniformed officers were assumed to be on patrol at any given time
- 45% of police were assumed to be on active duty patrol, translating to ~18 police agents in the model
- Tucson has approximately 5,000 reported burglaries each year, or ~13 per day
- Given geographic proportion, the region of Tucson modeled accounts for 20% of the total burglaries, or ~2.75 per day
- Of 50 interviewed jailed burglars, all had committed at least 20 burglaries over the previous three year period, with ~50% claiming to have committed over 100 [11]
- To obtain ~2.75 burglaries per day, ~50 burglar agents were needed, assuming agents commit 20 burglaries on average per year
- Roughly 13% of all burglaries are cleared, resulting in arrest or prosecution [16]

3.4 Computational Methods

Given several output parameters were tracked with respect to time, a pseudo-time stepping procedure was used, with relative time scales for each agent action. For efficiency, a global step size of 15 minutes was set, with burglaries lasting 45 minutes, work lasting 8 hours, social events consuming 2.5 hours, and time spent at home lasting 9 hours. Each simulation was executed for 18,000 steps, or the equivalent of 6-months real time. An embarrassingly parallel scheme was applied with agent multi-threading for computational acceleration. Simulations consumed approximately 25 minutes of wall clock time running on a quad-core workstation.

4. Verification and Validation

Verification and validation is a multi-step process between various domains in the real and simulated world. The following section examines how reality was perceived and modeled in this simulation.

4.1 Raw Data and Proxy Data Validation

Building attributes were initialized from raw census data. Given the census data was resolved only at the community level, Gaussian distributions were applied to introduce variance into the model. Plotting scripts were used to confirm that attributes were properly distributed. As an example, the house value map applied in the simulation is shown in Fig. 5a. Fig. 5b contains the raw census data, resolved only at the community level.

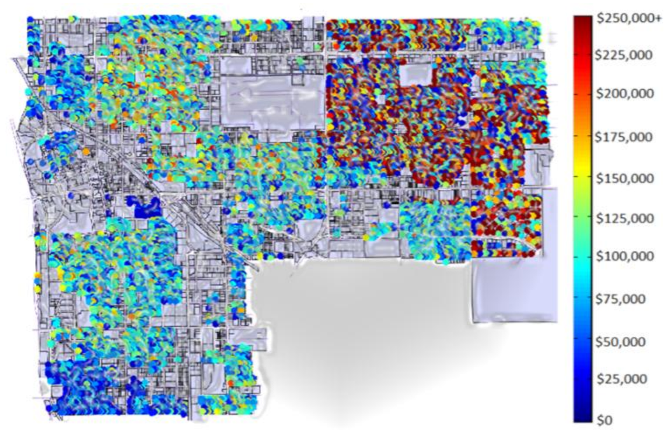

Fig. 5a: Simulated home values based on Tucson census

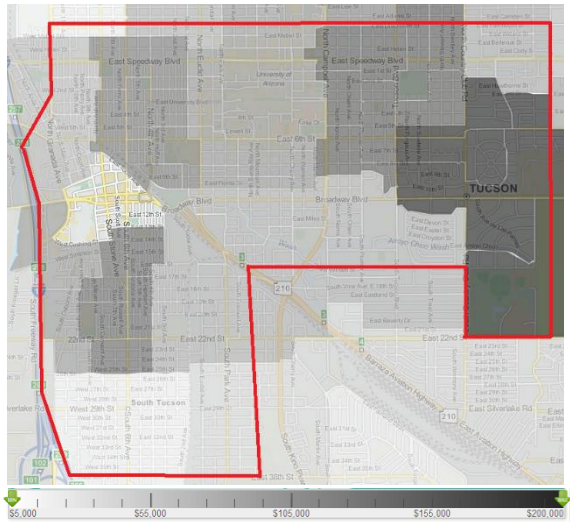

Fig. 5b: Raw home values from Tucson census data

4.2 Theory and Conceptual Validation

The nature of burglaries was developed based on social and behavioral publications. The conceptual theory employed in the model was validated based on the emergent characteristics displayed over long run simulations. Observed high crime regions matched historical data and intuition based on city layout. Fig. 6a and 6b compare spatially the distribution of burglaries from the SoS model with real crimes reported in Tucson from October 2012 through March 2013. Non-hardcoded effects such as compound burglaries in the same location and the average distance between a burglar's target and their personal residency matched trends gleaned from social papers on the subject.

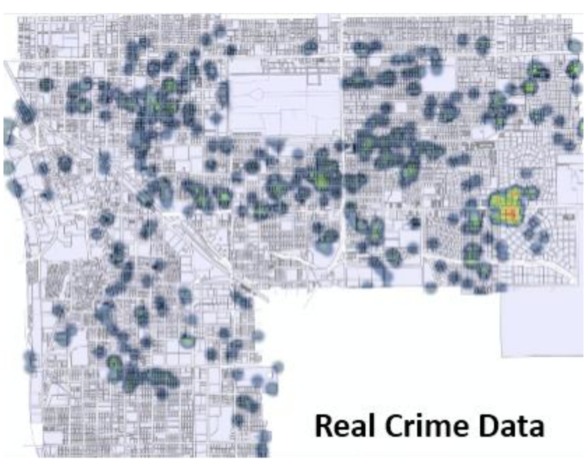

Fig. 6a: Real burglary data reported Oct. 2012-Mar. 2013.

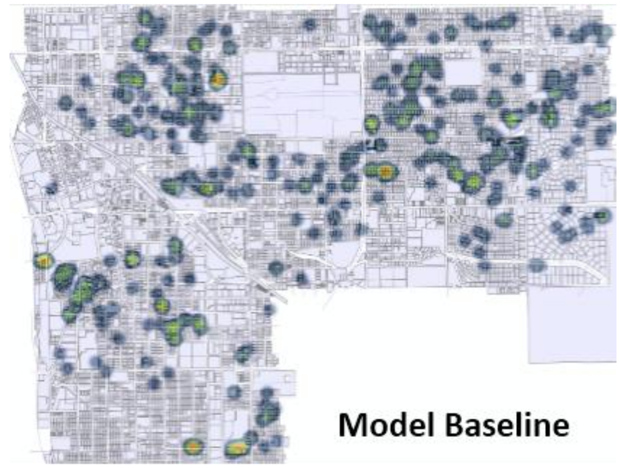

Fig. 6b: Six month Baseline Simulation Results

4.3 Operational Validation and Calibration

Once the simulation was trending correctly, the probabilistic distributions used to drive agents to burgle were tuned to match multiple metrics as described in the model assumptions. To comply with the Meltzer rules, a majority of the simulation parameters were held constant, with only a few probabilities and action wait times varied incrementally. [18] The number of burglaries per day, the ratio of criminals to police, and the success rate of police were chosen as the key parameters to be matched with real Tucson crime statistics. Duplicate runs were also performed to ensure long-run repeatability. Results of this calibration effort are provided in Table 2. All model values match remarkably well with the exception of the percent of agents who are high repeat offenders. This difference is largely attributed to the manner in which arrests occurred, which removed caught burglars directly from the simulation, replacing them with a newly initialized burglar with no arrest record.

Table 2

Comparison of key model outputs with real data

Metric	Real Data	Model Baseline
Burglaries per Day	2.75	2.55
Arrest Percentage	13%	12.2%
% of Agents who Commit 3+ Burglaries in 6 months	100%	100%
% of Agents who Commit 16+ Burglaries in 3 Months	50%	15%
% of Agents who Travel < 2 Miles to Burgle	50%	60%

4.4 Verification and Debugging

To ensure the model operated as expected, features were added incrementally and frequently tested. Significant feature updates were also vetted through group code reviews and pair programming sessions. Once a significant amount of complexity was added, more advanced analysis was required to keep track of all variables for multiple agents. A secondary code was developed to aid in graphical data visualization and included dynamic updates as the simulation executed. Additional post-processing scripts were used to organize information and analyze trends across multiple trial runs.

5. Results

5.1 Understanding Impacts of Road Structure on Criminal Patterns

Besides being a function of money and opportunity, burglaries are also dependent on the layout of roads in a given city. Statistically, burglars target familiar homes along major routes [11]. In the SoS context, a city's road structure can be viewed as a network of connections between different buildings, or nodes. Disabling or otherwise modifying the city road structure served as a method for analyzing the network topology of the city's resources. As of 2013, Tucson, Arizona is undergoing construction of a Modern Streetcar to usher patrons between two economic city centers. Construction of this railway has caused significant road closures in the downtown region, extending West and North of the nearby university [19]. Implementation of the road closures to support Modern Streetcar construction was simulated in the model by increasing the network weight of each closed road segment. Fig. 7 demonstrates the primary roads used by agents, with the highest density concentrated near the downtown Centro area. To study road closure effects on burglary, two scenarios were chosen to assess emergent behavior given the construction on major roads with different percentage closure. The scenarios were defined as:

1. *Closure of Downtown Route* – Construction on downtown segment of Modern Streetcar Route (approx. 20% closure)

2. *Closure of Downtown and West University Route* – Construction on downtown segment and connecting segment leading to the Western edge of the University of Arizona (approx. 55% closure)

Fig. 7: Road usage density from baseline scenario and proposed road closures: (Scenario 1) downtown route (Scenario 2) downtown to West university route

The effects of "rewiring" the street network are proportional to the extent of the road closure. By closing the roads near downtown (a critical thoroughfare) a 30% drop in burglaries per day was observed. The effect of this closure also played a significant role in the 36% drop in burglaries for scenario 2, where additional roads were closed to construct the West university route. The percentage of arrests varied between 11-14% for the two scenarios. This is a surprising emergent behavior, where the number of burglaries declined over a 6 month period due to road closures, with a constant police force. These results show that burglars were forced to share common routes with police, since both were subject to the road closures. These bottlenecks resulted in more frequent police encounters, greatly increasing perceived police presence and reducing burglary opportunities. Gross differences in crime density throughout the city are not evident in the Fig. 8 heat map results. Over the six month simulation period, burglars had the opportunity to traverse all parts of the map for work or socialization, thus committing a large percentage of homes to memory. In essence, area familiarity increased over long run times as more knowledge of the area was gained. Once the decision to commit a burglary was made, police encounters became the only deterrent.

Although burglary patterns were not observed to shift dramatically with the closure of major roads in Tucson, the effectiveness of police in the different jurisdictions changed notably. It was observed that the more frequent crimes were attempted in Jurisdiction 2, the more likely they were foiled by police.

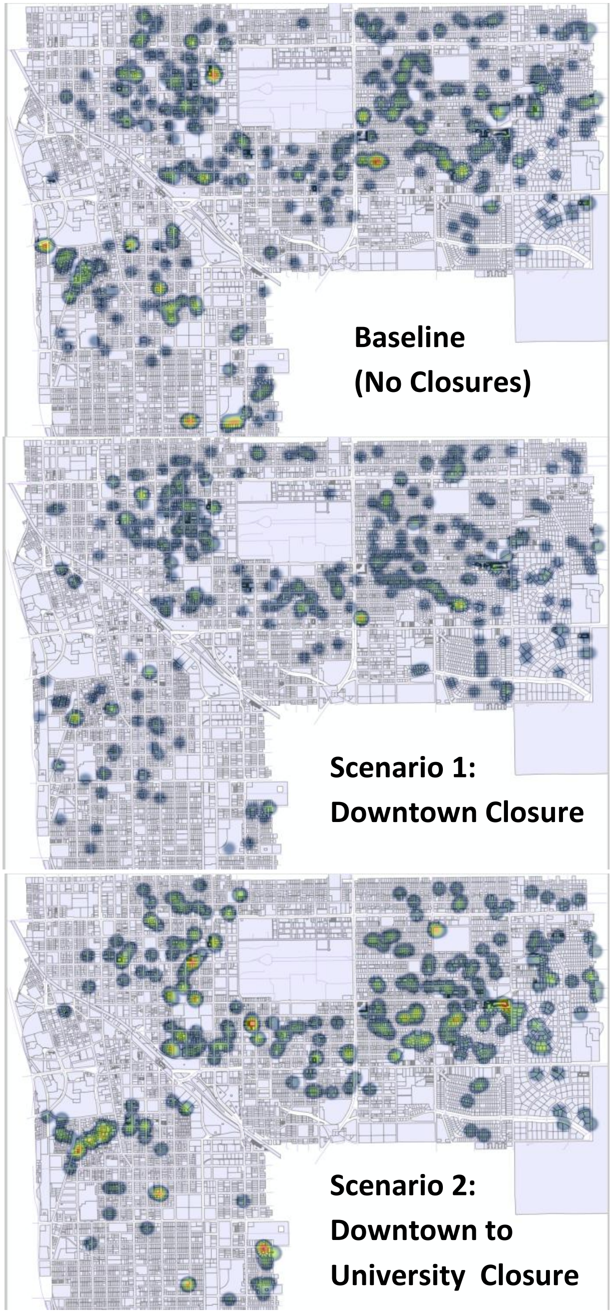

Fig. 8: Burglar heatmaps (crime plots) for road closure analysis

Table 3
Distribution of arrests by police jurisdiction

Distribution of Arrests Per Jurisdiction			
Jurisdiction	Baseline	Scenario 1	Scenario 2
1	27.6%	13.9%	33.3%
2	36.2%	52.8%	42.9%
3	36.2%	33.3%	23.8%

The closed roads comprised a small portion of the total network, but significantly extended the shortest paths to common destinations. Longer routes further increased the likelihood of police and burglar encounters. It should also be noted that the rigid SoS boundaries played a significant role in these results, by further reducing the number of alternate routes available to agents.

5.2 Assessment of Police Patrol Tactics on Residential Burglary

In addition to studying changes in road network topology, an investigation of police patrol procedures was performed. In the baseline model, police agents were scheduled to patrol randomly within their jurisdiction, and frequently return to their assigned station. Spatially, this maintained a high concentration of police in the immediate vicinity of police stations, naturally eliminating local crime. For implementing intelligent patrol tactics, police agents were provided access to a log of recently burgled locations. During routine patrols, police were assigned a fixed probability of travelling near previously burgled homes. Although this change was implemented at the individual level, it served to redistribute the police force on a more aggregate level, and was not actualized as an advanced criminal pursuit mechanism. Fig. 9 demonstrates the effect of patrolling high crime regions on daily burglary and arrest rates. In addition, Fig. 10 shows the displacement of crime due to more intelligent patrol procedures.

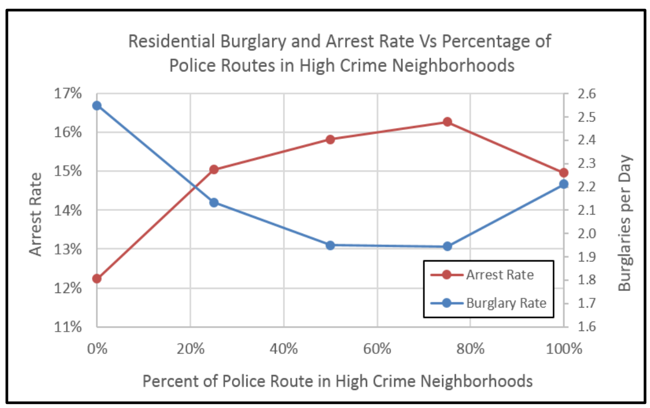

Fig. 9: Burglary and arrest rates for varying degrees of police patrol awareness

As the percentage of police routes dedicated to patrolling high crime vicinities increased from 0% to 75%, a marked decrease in daily burglary rates became evident. As expected, a small increase in arrests also occurred, given the increased likelihood that police would encounter criminals in common crime zones. Less expected, was the behavior that appeared when police agents began devoting 100% of their patrol route to high crime locations. As law enforcement became heavily concentrated in specific neighborhoods, a noticeable increase in burglary rate occurred, accompanied by a decrease in arrests. This result is due to the over saturation of police near frequently burgled homes, which left many regions of the map unmonitored. Burglars were deterred in areas of high crime, but migrated to neighboring communities where police exhibited less presence.

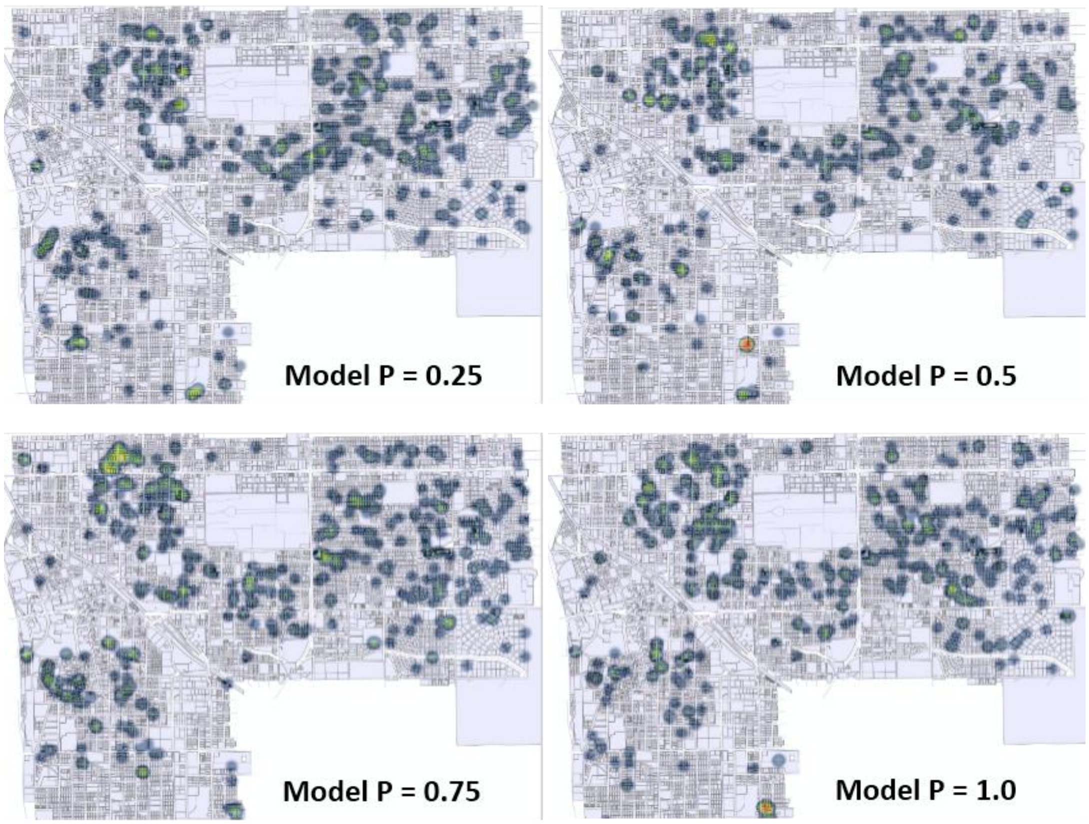

Fig. 10: Burglary heatmap for varying police patrol awareness where P is probability of patrolling burgle prone area

6. Conclusions

An agent-based model has been coupled with a virtual environment and geography representing the modern-day West-Central Tucson Arizona. Real world census data and statistics were used to initialize environmental parameters, while others were used as metrics to aid in concept validation. After developing a baseline proxy-world, topological disruptors were introduced in the form of road closures, and police patrol redistribution. It was found that both methods displaced criminals while increasing encounters with law enforcement. Due to the relationship between property value and home security level, house values were less of a driving factor than originally hypothesized. Median value homes were most frequently burglarized, where reward was high and security risk low.

Of the two case studies performed, police patrol tactics had the greatest impact on arrest rates over a 6-month period, while road closures had greater effect on city-wide burglary rates. In the police patrol simulation, burglary rates decreased while arrest rates increased as patrol routes were shifted into high crime zones. As law enforcement became overly saturated in burglary prone areas, a decrease in police effectiveness was evident and accompanied by a displacement of crime. In the road closure scenarios, similar trends were evident and likely exaggerated by the rigid simulation boundaries. Disruptions in agent routes caused a larger frequency of police encounters. With an increased perception of law enforcement, overall burglary rates declined despite a constant number of police agents. Simulation results demonstrate the efficacy of the approach and serve as a proof of concept for predicting spatially and temporally resolved burglary response to fundamental city SoS changes.

7. References

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8. Appendix

Commit History (Realized Schedule)

Our group used distributed version control (Git) to simultaneously work on the simulation. We kept the master repository in the cloud using the Bitbucket online hosting service. After finalizing any edits to the code, each member would push revisions up the main branch, where the version control software kept track of all changes, and monitored any conflicts. Before starting work again, members would pull down the latest version to stay up-to-date. Using version control allowed the group to work in parallel and if any errors or bugs were introduced to the repository, it could always be rolled back to a previous version. Below is a list of “commits” made to the master repository by all 3 members. The repository can be pulled down in the public repository found on Github:

Full Program can be Downloaded Online at:

ZIP downloadable: https://github.com/jcchin/AAE560Team15
or using Git: https://github.com/jcchin/AAE560Team15.git

Follow the README to install and run.

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Author	Commit	Message	Date
Jeffrey Chin	d159d06	Added RoadTravel Heatmaps for road closure scenarios	19 hours ago
Dan Heacock	ef37c5e	Ran two road closure runs and saved results	2 days ago
Jeffrey Chin	0fdc867	Compiled Processing w ceiling normalization	4 days ago
Jeffrey Chin	5217cdf	Merge remote-tracking branch 'refs/remotes/origin/master'	4 days ago
Jeffrey Chin	f3198e0	processing	4 days ago
Christopher H…	0be6607	updated results	4 days ago
Jeffrey Chin	e02d8f1	consistently normalized heatmap images, plus additional runs from Chris	4 days ago
Dan Heacock	d3f16d7	Ran two identical runs for road closure scenario 2 (downtown to UofA)...results included	4 days ago
Christopher H…	f348486	baseline settings to match burglary and arrest rates	4 days ago
Jeffrey Chin	c6e19b3	"Clear Button" works now. Fixed 18k run, compiled latest processing version	5 days ago
Dan Heacock	c7f6a1b	performed 18k run with maplimit = 200...added to results...	5 days ago
Jeffrey Chin	f7518c6	clean-up 2	5 days ago
Jeffrey Chin	596e5ec	Clean-up	5 days ago
Jeffrey Chin	825deb2	Results Folder	5 days ago
Christopher H…	3a61e02	Increase heap allocation	2013-04-22
Dan Heacock	60c4428	Minor update for road closure, added globalvar for max memory map size	2013-04-22
Christopher H…	c81770f	Distributed police evenly between jurisdictions, reduced the number of police from 40 to 20.	2013-04-21
Jeffrey Chin	40764a7	updated executable	2013-04-21
Jeffrey Chin	840f8ee	minor changes	2013-04-21
Jeffrey Chin	532e6e8	initializeLevels() now gives a non-zero starting oppLevel (otherwise the alarm sets off police	2013-04-21
Jeffrey Chin	9aa59a8	global enable prints, integer verbosity	2013-04-21
Jeffrey Chin	1397b93	small update	2013-04-21
Jeffrey Chin	599907d	Flipped BurgleP comparison, removed unecessary print statements, reduced burgleP	2013-04-21
Dan Heacock	c4d40c6	added road closure ability, set smartPick to false (For baseline runs)	2013-04-19
Jeffrey Chin	d3cf5da	Fixed Processing Probability Bar Bug, increased read robustness, normalized histogram	2013-04-17
Dan Heacock	5325617	ignore this	2013-04-16
Dan Heacock	2f20e88	Added oppLevel check when arriving at house and make sure police don't pick same	2013-04-16
Christopher H…	22eeef3	Completed code review, updated Police agent to have a random probability of patrolling near	2013-04-16
Christopher H…	7318ebd	fixed bug in smart selection of buildings by police	2013-04-15
Jeffrey Chin	9f226de	Merge remote-tracking branch 'refs/remotes/origin/master'	2013-04-14

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625e33423b5e

Author	Commit	Message	Date
Jeffrey Chin	625e334	Burgle Histogram and etc	2013-04-14
Christopher H…	38f13dc	Fixed and cleaned up some code in burglarAgent that I think wasn done incorrectly. Added tw	2013-04-14
Jeffrey Chin	d38f6d3	Merge remote-tracking branch 'refs/remotes/origin/master'	2013-04-14
Jeffrey Chin	35b1a4d	Improved Processing read robustness	2013-04-14
Dan Heacock	2e64619	Added output files: roadtravel.txt, junctiondata.txt, and agentresults.csv	2013-04-13
Dan Heacock	79b457d	Updated some global vars and timing	2013-04-12
Dan Heacock	e3768c8	Create global variables for hard coded values and add "Real" Tucson crime data	2013-04-09
Jeffrey Chin	f9c250d	Heatmap export + % robbery stuff	2013-04-07
Jeffrey Chin	512ec1d	Big Processing Update, Context Manager Output function	2013-04-03
Jeffrey Chin	1af3f0e	Merge remote-tracking branch 'refs/remotes/origin/master'	2013-04-03
Jeffrey Chin	4058b47	Added multiple windows and heatmap for burgleAnalyze	2013-04-03
Dan Heacock	3f7e207	fixed bug in burgTarget, fixed moneyincrement, added globals, added removerows.m, and	2013-04-03
Dan Heacock	bc75908	Cleanup, fix bug for occupied house, changed security logic, output buildings to results file,	2013-04-02
Christopher H…	fa8b4ec	Added feature where a burglar is caught. Returns the agent home and resets their money an	2013-03-31
Dan Heacock	ce47370	Fixed null bug where agents could not find house to burgle	2013-03-31
Dan Heacock	313cfcc	Updated burglar money increments and some "opportunity" based changes	2013-03-30
Christopher H…	c76f814	Fixed jurisdiction bug in context manager. Agent now patrol their assigned jurisdiction. The	2013-03-29
Dan Heacock	7899038	Updated GIS Police data and implemented jurisdictions (although needs some more work)	2013-03-29
Dan Heacock	89e6d59	Major merge of East and West Philosophies	2013-03-28
Jeffrey Chin	54fef9e	opp level, burgle awareness	2013-03-28
Jeffrey Chin	cfbfe46	Functional Heatmap Added!	2013-03-19
Jeffrey Chin	9704738	Add percentage bars and map image to processing	2013-03-18
Christopher H…	135d064	Added memory map. Agents now build an awareness map as they travel and select burglary	2013-03-16
Jeffrey Chin	4f77507	fix5 + sketch	2013-03-15
Jeffrey Chin	285aca6	fix4	2013-03-15
Jeffrey Chin	54433ce	fix3	2013-03-15
Jeffrey Chin	d516647	fix2	2013-03-15
Jeffrey Chin	f20a664	fixing burgleAnalyze	2013-03-15
Jeffrey Chin	e065632	added 3rd optional path	2013-03-11
Jeffrey Chin	e9445e3	Reworked burglar step behavior, added dynamic agent vizualization executable and file writin	2013-03-11

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229ed1b78da0

Author	Commit	Message	Date
Jeffrey Chin	229ed1b	Added Police init box (Random 1 4)	2013-03-10
Dan Heacock	f438a93	New GIS Data	2013-03-09
Christopher H...	e845daf	Merge remote-tracking branch 'refs/remotes/origin/master'	2013-03-07
Christopher H...	09549cb	Updated Police agent behavior, they now are initialized at a police station (type=4) and	2013-03-07
Jeffrey Chin	99d03be	Fix York Path Error, added error debug to README	2013-03-07
Christopher H...	4dc8b90	Merge remote-tracking branch 'refs/remotes/origin/master'	2013-03-07
Christopher H...	fea894e	extra	2013-03-07
Christopher H...	b3dcac4	Added baseline agent behavior to follow flow chart	2013-03-07
Dan Heacock	baf9865	updated tucson	2013-03-06
Jeffrey Chin	c792a71	Added Basic Social fluctuations, fixed path bug	2013-03-05
Jeffrey Chin	fbc0fc6	Added Dan's GIS map to BurglaryABM	2013-03-05
Jeffrey Chin	d86dec8	created git_ignore for all metaData	2013-03-05
Dan Heacock	758f3cd	Added new subfolder for GIS data	2013-03-04
Dan Heacock	2f467fa	Added Simplified GIS Data	2013-03-04
Christopher H...	43d4052	new Burglary Sim	2013-03-03
Christopher H...	a65c14d	deleting old repast_city	2013-03-03
Christopher H...	bd5d1bf	I hope this works	2013-03-03
Jeffrey Chin	f5caa51	updated burg city	2013-03-03
Jeffrey Chin	6ba56f1	meta2	2013-03-03
Jeffrey Chin	257344f	Added Data viewer to Jzombies	2013-03-03
Jeffrey Chin	c03dec7	random metadata	2013-03-03
Christopher H...	7431cfa	Uploading repast_city bankers with some modifications to burglar agents	2013-03-03
Jeffrey Chin	a9e9c8d	Added JZombies Tutorial, written by Jeff	2013-03-03
Jeffrey Chin	5b98742	Add RepastCity3 to repo	2013-03-03
Jeffrey Chin	57012df	lala added	2013-03-03
Jeffrey Chin	8ff48e7	updated README	2013-03-03
Jeffrey Chin	56a9c44	first commit!	2013-03-03

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Division of work:

Programming:
Dan Heacock performed all pre-processing of GIS data that was used to initialize the simulation to match the city of Tucson. Together, Chris Heath, Jeff Chin, and Dan developed the main behavior and decision process for burglars and police agents. Chris further developed agent memory maps, Jeff further developed agent inter-awareness. Dan implemented all security system functionality. Jeff developed all of the post-processing code using the Processing language. Chris and Dan ran a majority of the final simulations, while Jeff was responsible for version control.

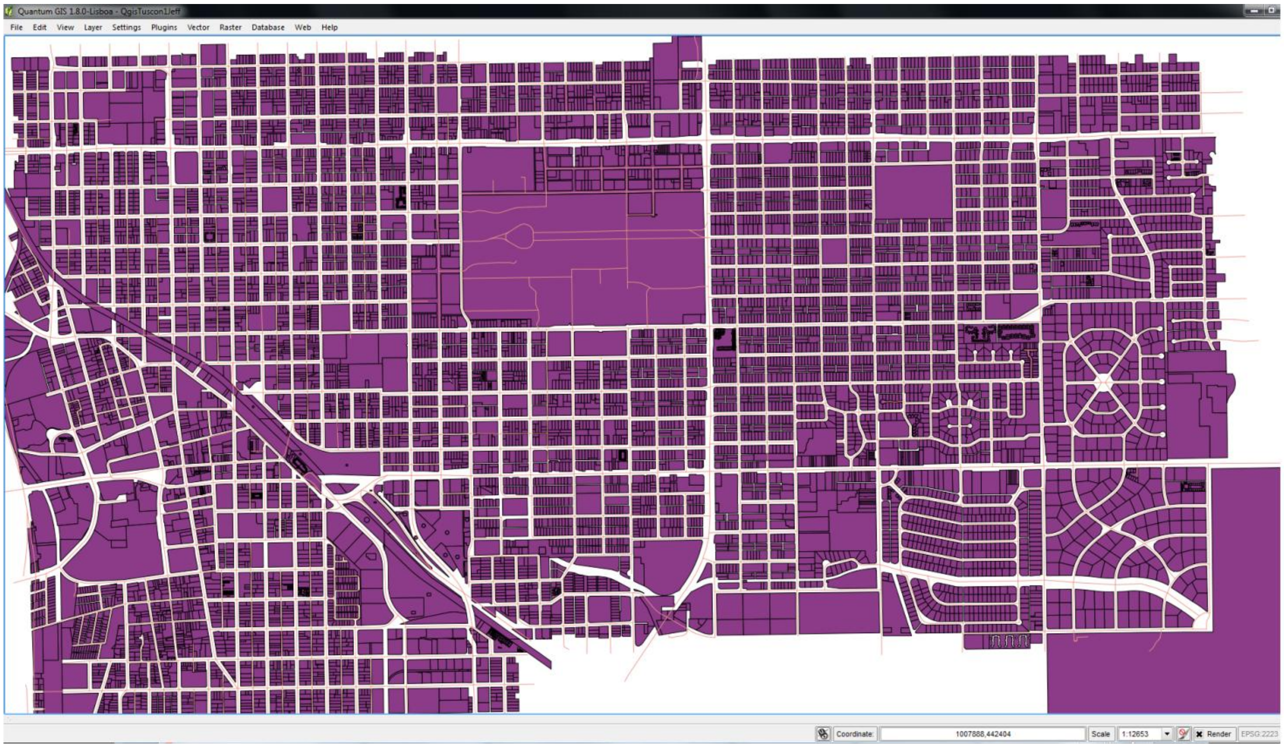
Writing:
All writing was composed and compiled using google drive, allowing all three member to edit and contribute simultaneously. All three members contributed equally to writing and editing content, with Chris responsible for final revisions.

Slides:
Slides were developed together using google drive. Dan recorded the audio.

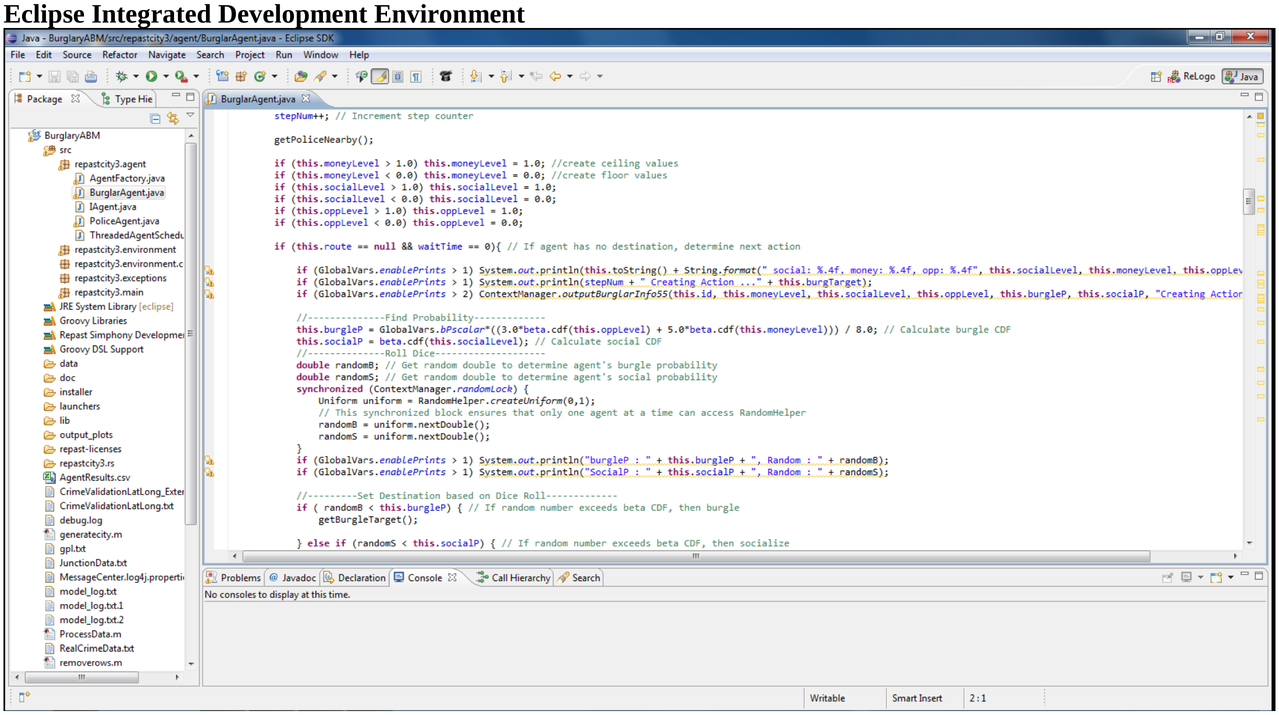
Collaboration Techniques:Beyond Google Drive and Git Version control, the team regularly emailed and attended Google “Hangouts” allowing the team to video chat and screen share.

Screenshots

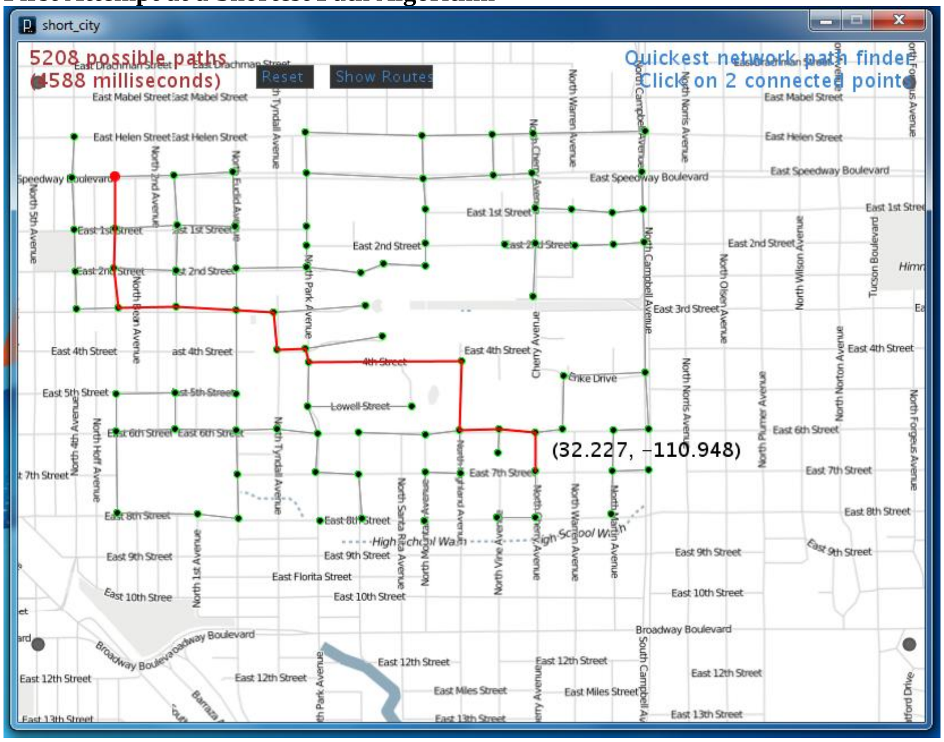
GIS Screenshot:



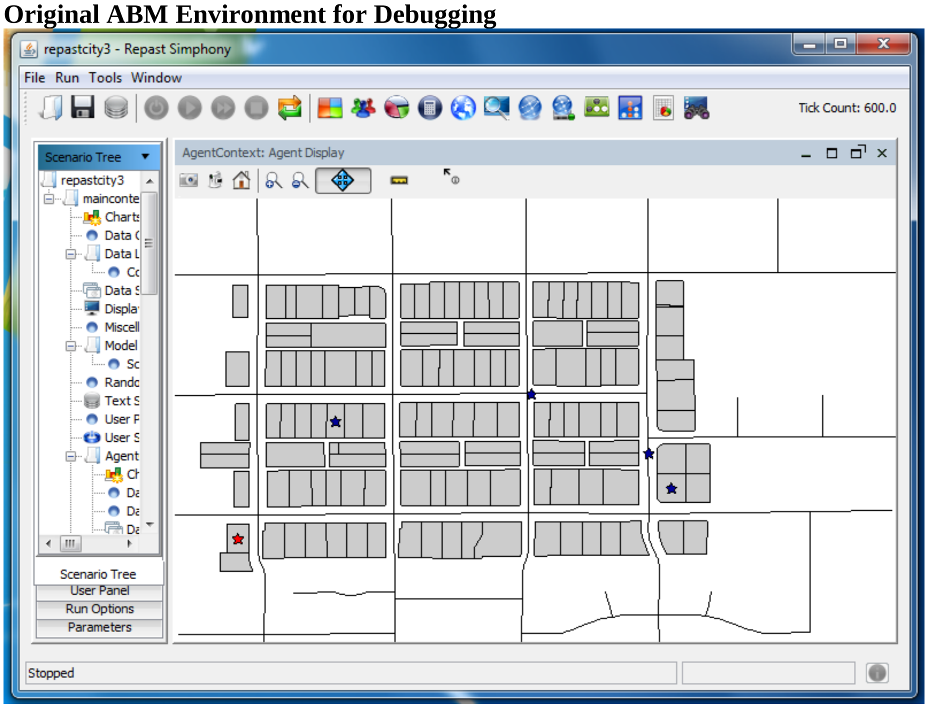
Eclipse Integrated Development Environment



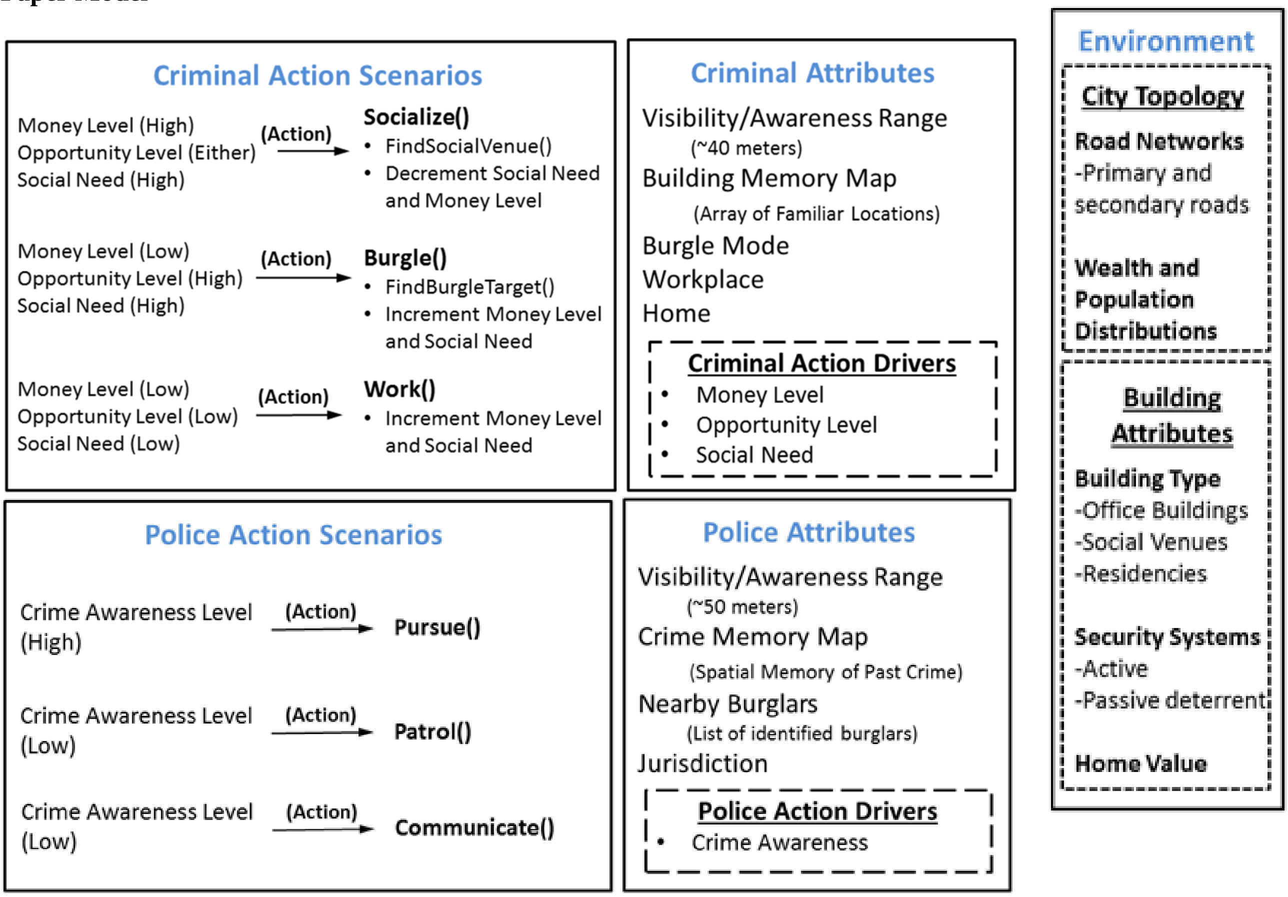
First Attempt at a Shortest Path Algorithm



Original ABM Environment for Debugging

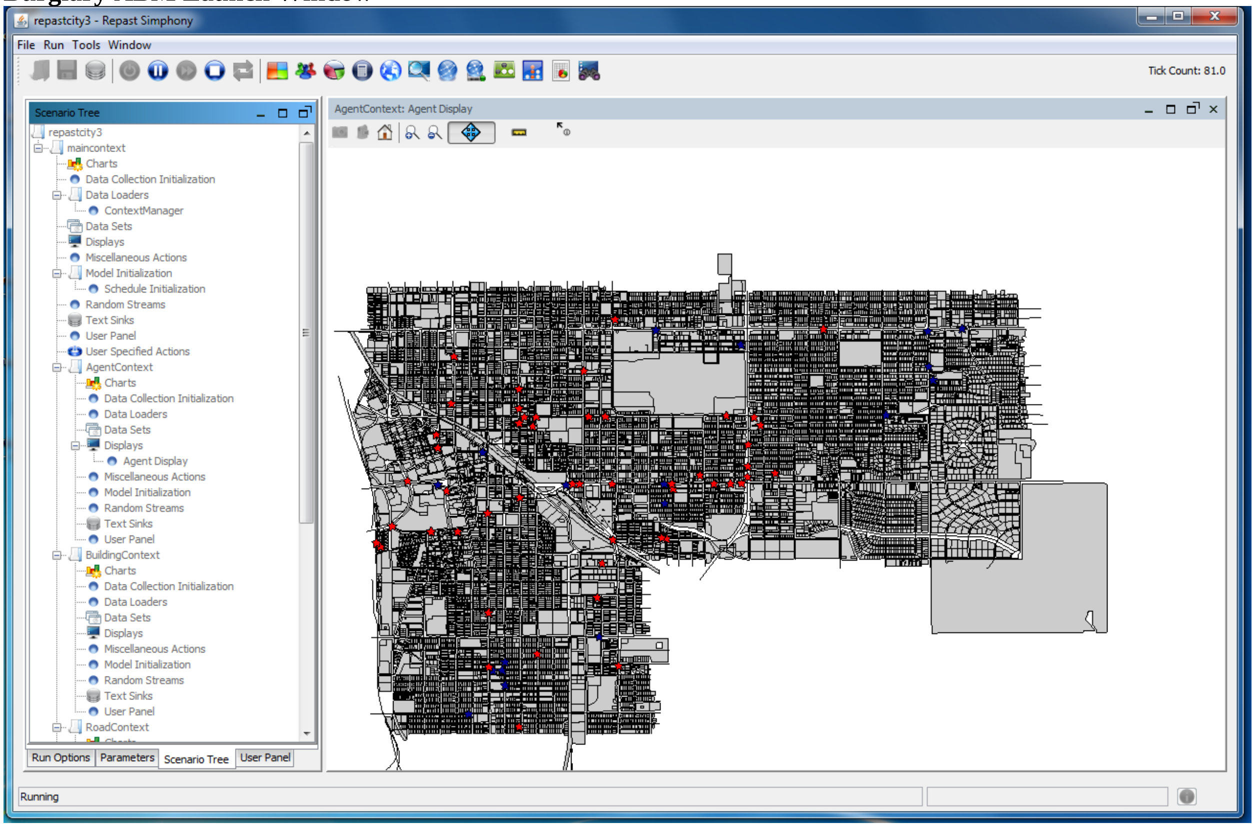


Paper Model

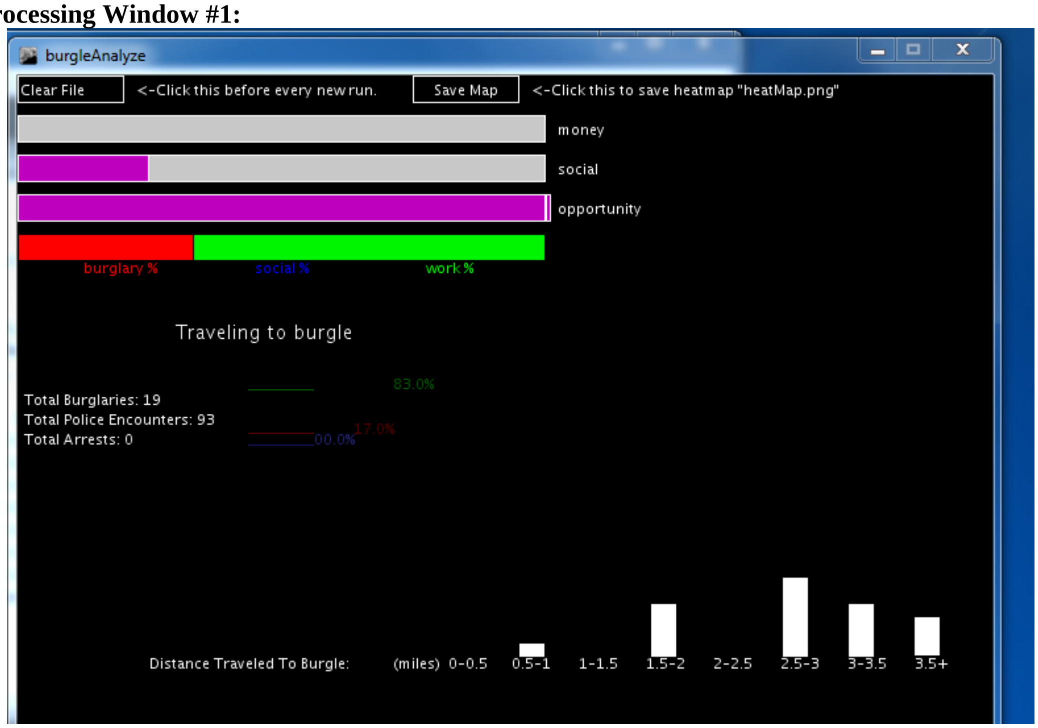


Regular Team 15 Google Hangout

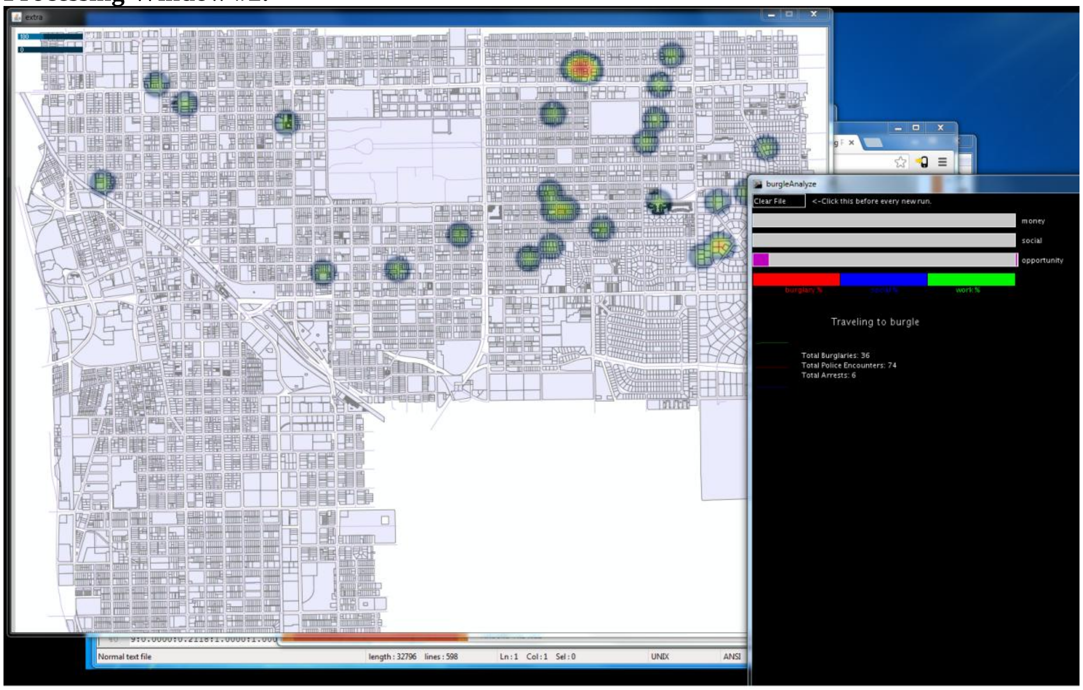
Burglary ABM Launch Window



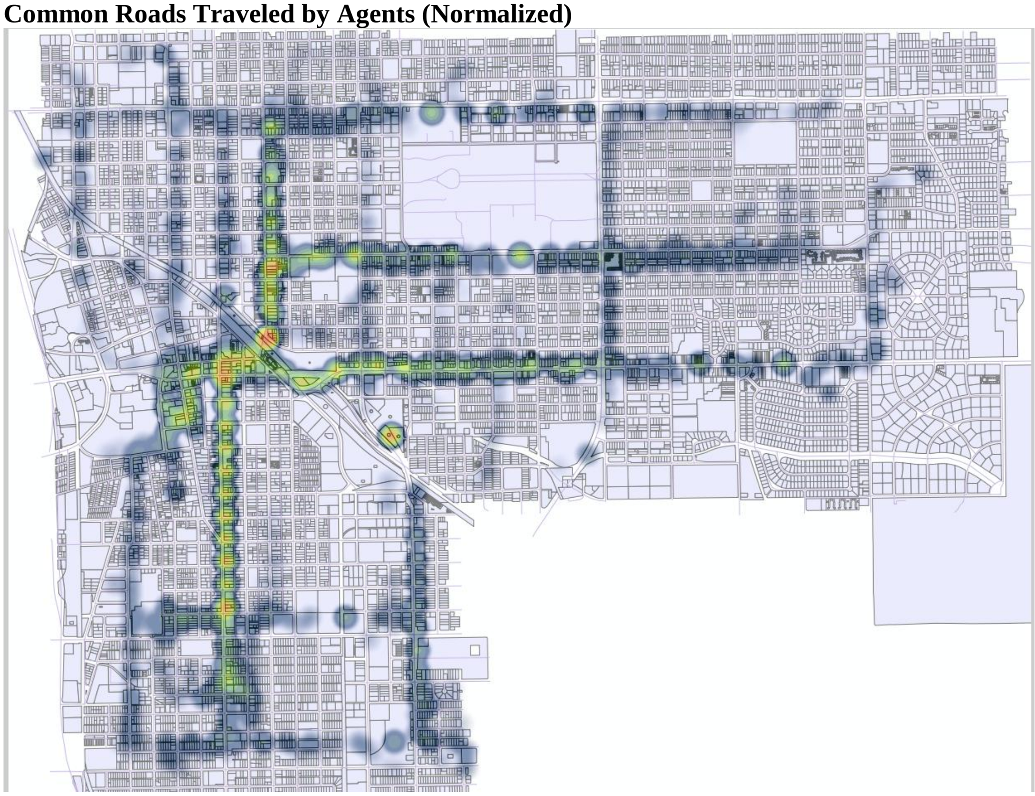
Processing Window #1:



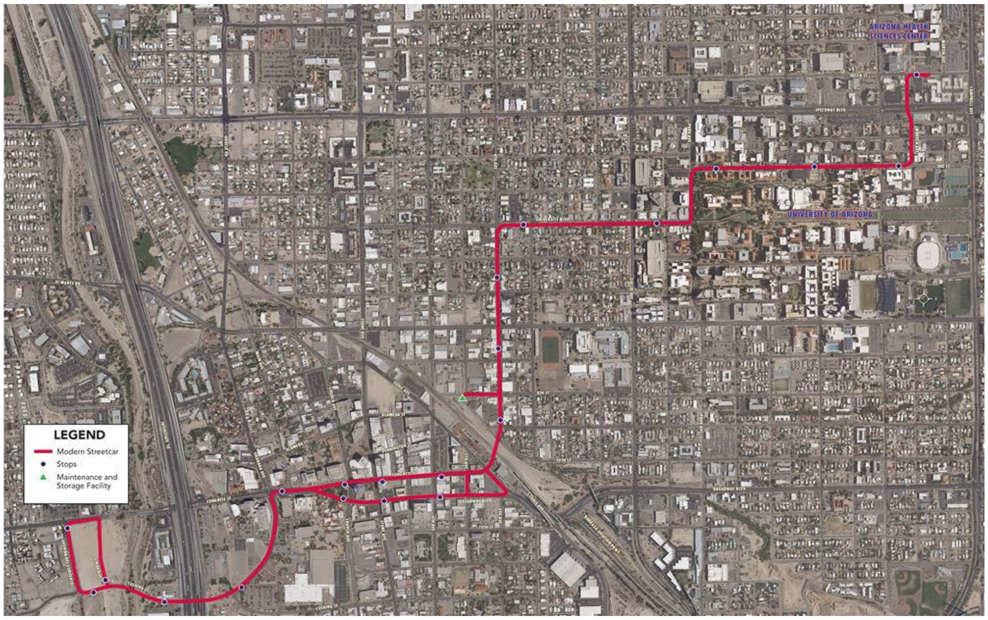
Processing Window #2:



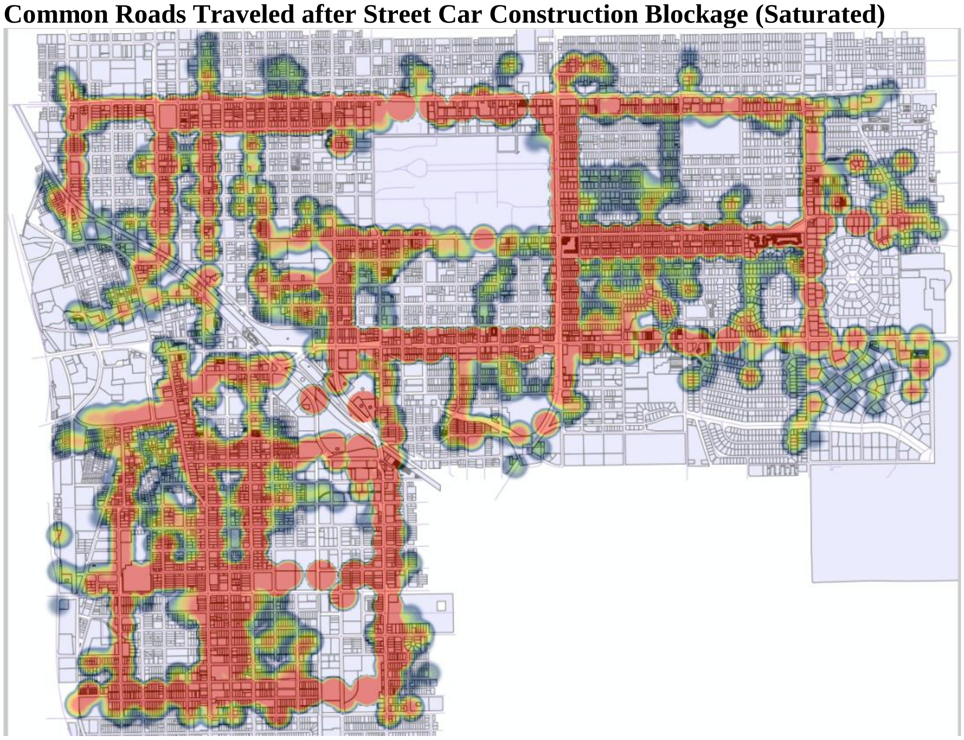
Common Roads Traveled by Agents (Normalized)



Modern Streetcar Route

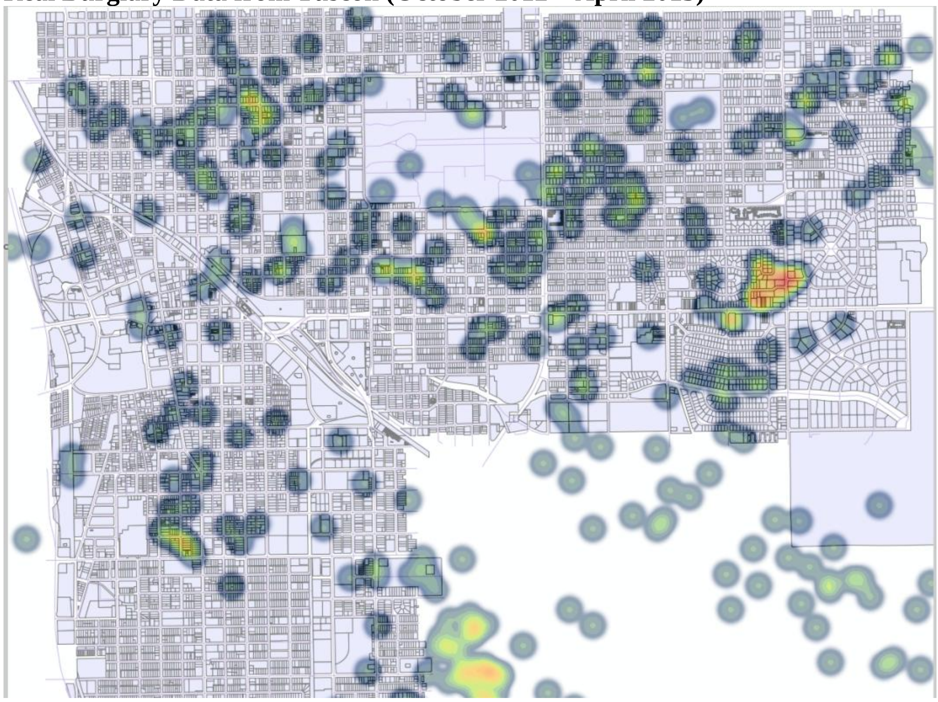


Common Roads Traveled after Street Car Construction Blockage (Saturated)

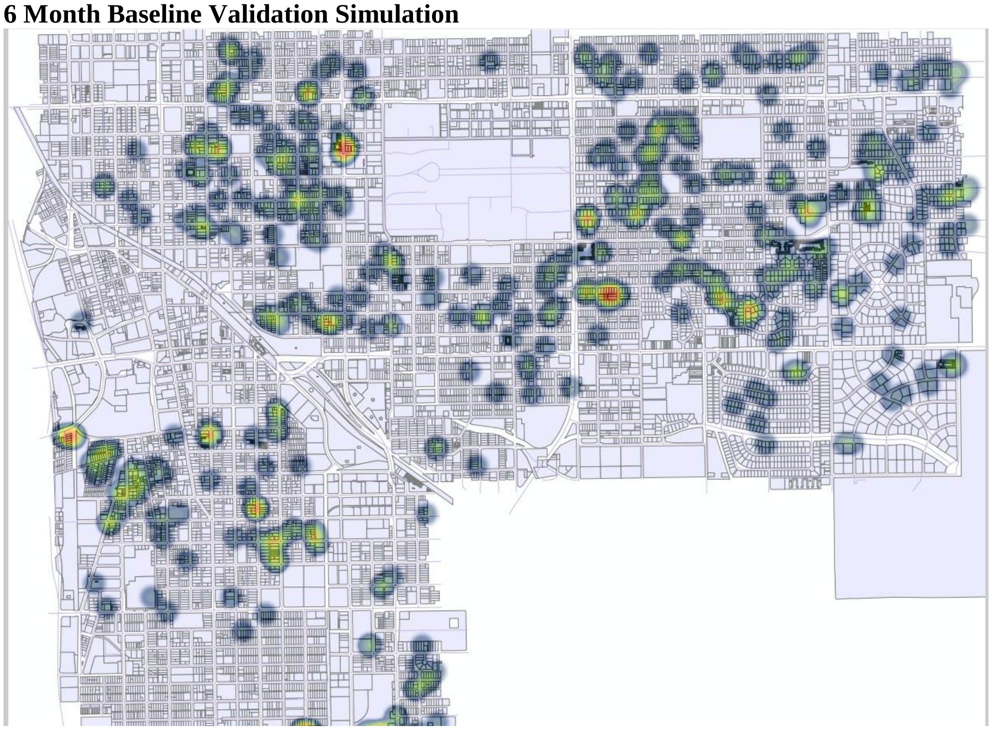


Heat Map Results

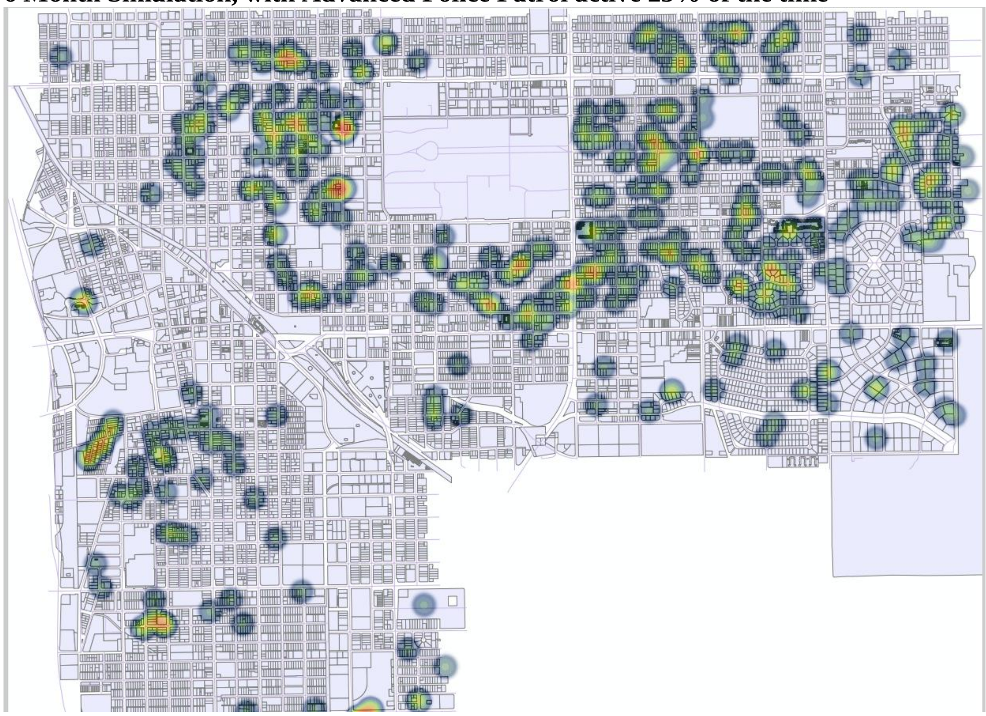
Real Burglary Data from Tuscon (October 2012 – April 2013)



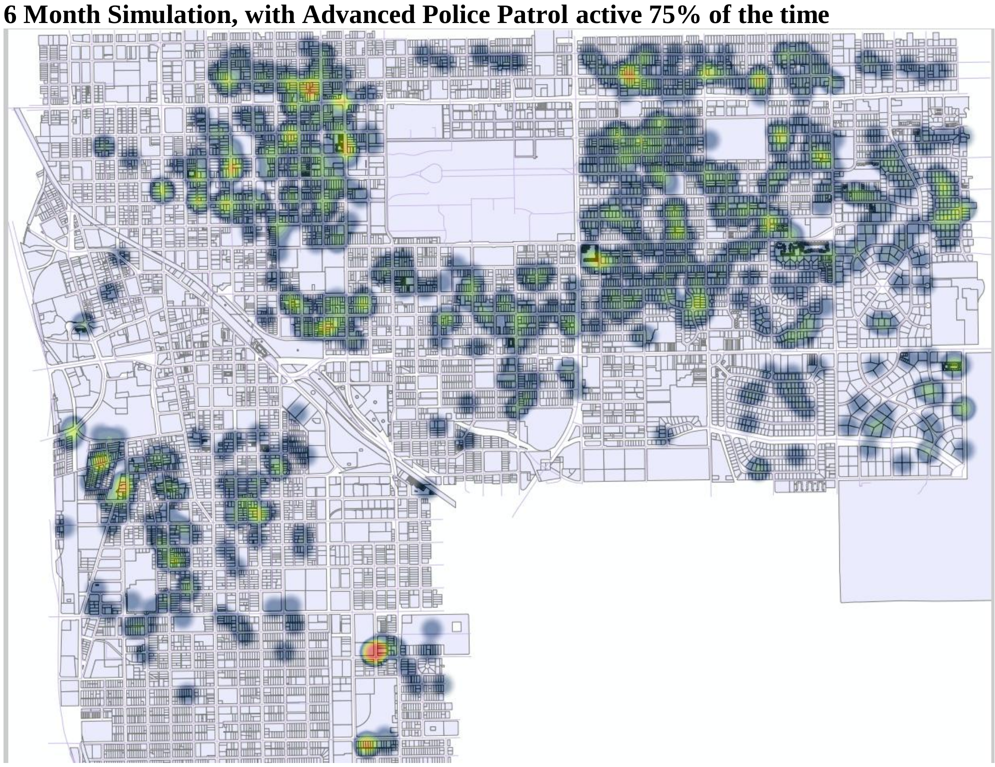
6 Month Baseline Validation Simulation



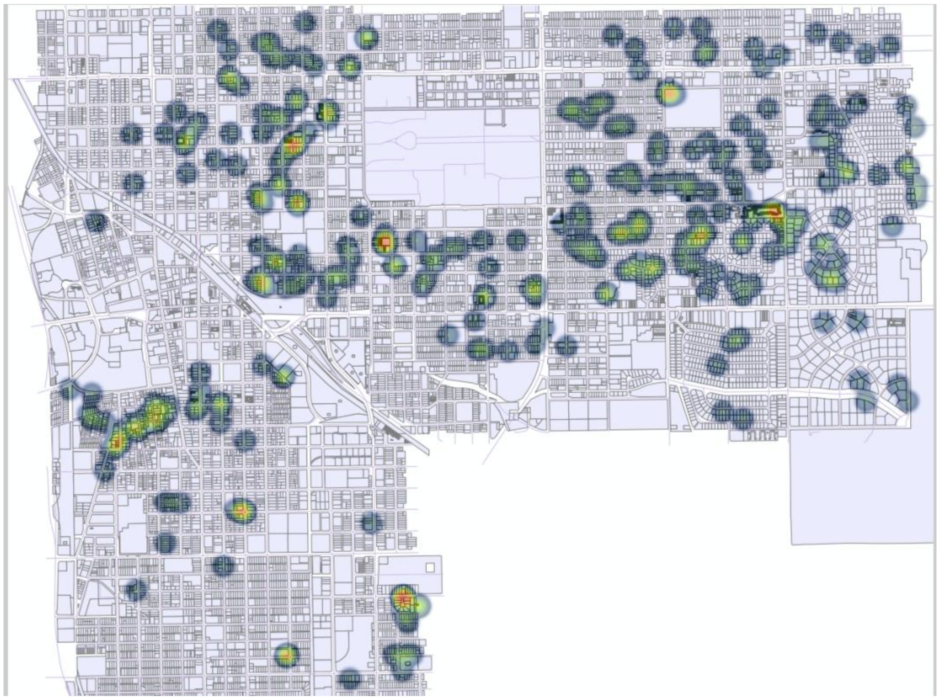
6 Month Simulation, with Advanced Police Patrol active 25% of the time



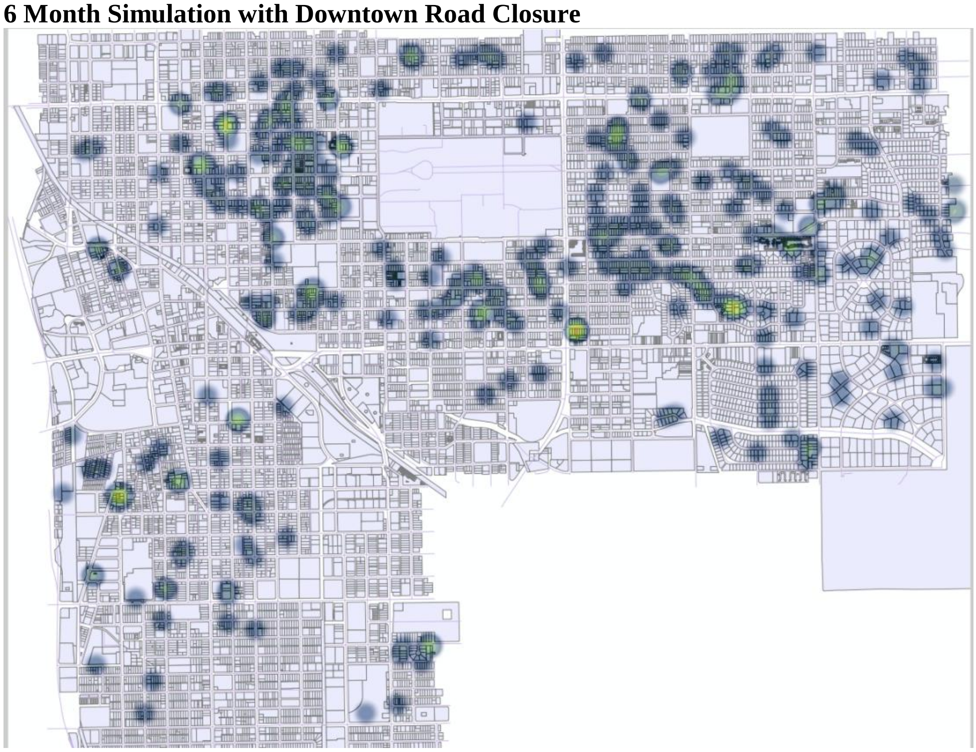
6 Month Simulation, with Advanced Police Patrol active 75% of the time



6 Month Simulation with Street Car Road Closure



6 Month Simulation with Downtown Road Closure

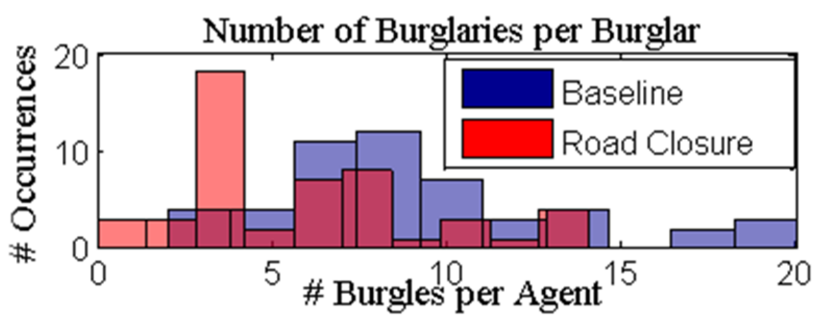


Tabularized Results

Burglar Agent Action	Simulation Wait Time (hours)
Burglary	0.75
Social Event	2.5
Work	8
At Home	9

Metric	Real Data	Model Baseline
Burglaries per Day	2.75	2.55
Arrest Percentage	13%	12.2%
% of Agents who Commit 3+ Burglaries in 6 months	100%	100%
% of Agents who Commit 16+ Burglaries in 3 Months	50%	15%
% of Agents who Travel < 2 Miles to Burgle	50%	60%

Histogram of Burglary Frequency Distribution



Future Work

- Upgrade police pursuit functionality
- Add additional community layer parameters, such as school networks, or neighborhood watch programs.
- Enhance the dynamic helper program (Processing) to better visualize multiple agents simultaneously
- More advanced metrics for describing criminal migration
- Batch file launching capabilities, for large sets of simulations
- Stand-alone launch capabilities for users without Repast or Processing
- Incorporation of game theory models into the burglary decision making and police patrol routes