A Systems Approach to Understanding Artificial Night at Light

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1 Executive Summary

Increasingly, news of climate change and global warming have dominated scholarship and media outlets. Exposure to such topics has warned the public of man-made harm to the environment, like air pollution and greenhouse gas emissions, yet one sector of anthropogenic pollution, light pollution is often overlooked. Awareness around this topic stems from education, policy and research. This issue which intersects ecological and social variables, is thus best studied under a systems approach, in which robust interdisciplinary perspectives are considered and analogously will warrant response from those in many fields. Contemporary studies of systems approaches frequently use agent-based models (ABM's) and techniques from network analysis. My project aims to pull from ideas in topology, ecology, and policy analysis to modify and strengthen light pollution policy in the contiguous United States.

2 Introduction

Systems theory, which describes the behavior and interactions of agents within a system, pulls from virtually all fields of academia. Coined by Australian biologist Ludwig von Beffalny, systems theory , "should be an important regulative device in science, to guard against superficial analogies that are useless in science and harmful in their practical consequences." It is the scientific movement against the advent of scientific reductionism and the call to view phenomena more holistically. Systems theory argues, as the Greek philosopher Aristotle puts, “The whole is greater than the sum of its parts”. Under the field of general systems theory is a set of systems known as Complex Systems of Complex Adaptive Systems. Complexity, which within scholarship has become ambiguous, refers to a system which is composed of multiple and interconnected parts and looks to prediction instead of explanation. Complex systems are often difficult to describe and look to analytic techniques to understand them holistically. I defined light pollution as a complex system, as it is a problem of the intersection of ecological and social dynamics. Complex systems are ultimately identified by 4 characteristics, first, they exhibit self-organizing behavior, or organization ultimately emerges from complexity, second, they are non-linear, in other words a change to one component will have an effect on the system on a varying scale, huge, small or even none at all. Finally, they have a chaotic dynamic that ultimately becomes more ordered with time, and finally they show emergent behavior, or the collective and often unexpected behavior demonstrated by the mix of interacting components within a system. Emergence also figures its way into self-organization, in a bottom-up manner, where complexity emerges at the initiation of a system and gradually grows into nonlinear interactions between components or agents of a system, from here as a system grows increasingly complex, order surfaces. Some systems, and specifically the systems problem of Light Pollution are also adaptive, which means they change with perturbations, or disruption to the system to maintain an invariant or unchanging state, which in the case of light pollution would be the propagation of artificial light, by altering behaviors or structures, collectively known as properties within the system. Such properties of light would be its, duration, scattering, intensity and spectrum.

3 Background

3.1 ALAN

Artificial light at night or what I will consistently refer to by its acronym, ALAN, is the leading driver of light pollution and a component of a my system that describes light pollution. ALAN, plays a significant role in light pollution: as Dark Sky international reports, “Skyglow fouls the night sky for more than 80% of all people and more than 99% of the U.S. and European populations.” Or as the authors on a recent study of light pollution summarize, “With an estimated annual average increase of 9.6% (estimated based on citizen science data), light pollution is one of the most pressing drivers of current global change, and it has become increasingly clear that the loss of the night has serious psychological, health, socio-economic and ecological consequences." ALAN is a form of "anthropogenic pollution", or pollution powered by human activity, that often disrupts the biological rhythms and in a systems view, the entire ecosystem. Humans, coincidentally are the prey of their own creation, as ALAN has detrimental effects on humans such as messing with circadian rhythms and sleep patterns.

Figure 1: ALAN

3.2 Emergence and the Behaviors of ABM Ecological Systems

Emergent behavior is the emergence of order from complexity within a system and ultimately gives us insight into the dynamics of a system. Emergent behavior comes in many forms and is separated into two categories, strong emergence and weak emergence. Strong emergence, which came out of the movement of British emergentism in the 1920s and refers to a more philosophical understanding of emergence, that is not deducible. Weak emergence on the other hand, is the rise of high-level phenomenon from low-level domain that is deducible. It is thus this weak emergence phenomena that I am looking for. Weak-emergence often appears in the form of patterns, an example of which is in Conway's game of life, where particular patterns like the toad and glider emerge from the chaotic dynamics of Conway's game.

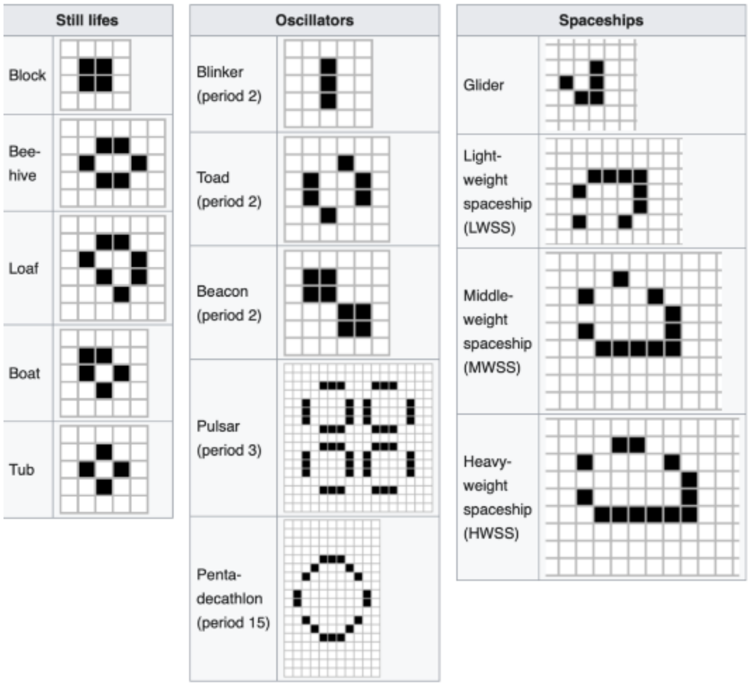

Figure 2: Conway's game of life emergent behaviors

My process of extrapolating these patterns and emergent behavior is similar in that it looks at patterns within the network representation of my model, by first analyzing the dynamics of the model. The underlying techniques are degree centrality, or the number of unique relationships or links a node has, betweenness centrality, or the measure of influence nodes have within a network, closeness, how connected a node is, eigenvector centrality, the discovery of central nodes, clustering tests, to cluster nodes into patterns, centrality tests, which once again identify central nodes, degree distribution or the number of connections per node, tests, modularity tests, or how well a network can be partitioned into modules, community detection algorithms, or the clustering of groups within the network and finally the number of connected components within a network.

3.3 Network Theory

Yet these metrics are virtually meaningless without proper introduction to the topological structures and properties of networks that make them so helpful in analyzing the emergent behavior of a system. Specifically, my model represents a socio-ecological network, or the connection of social(man-made) variables like light, and the ecological agents of the Orb-Web Spider ecosystem. Network Theory, which translates agents as nodes and interactions between agents as edges is advantageous because of its rich topological structure, from which patterns like modules, communities etc. reveal underlying behaviors and properties of a system. In the biological realm, Network Theory has seen growing applications in molecular biology as well as macro-scale ecological systems(in tandem with anthropogenic variables), like the one I sought to analyze. Ecological networks often characterize interactions between nodes as trophic or symbiotic, either a classical predator-prey relationship or coexistence respectively.

4 Model

In the vein of my systems approach, I created a system, an ecosystem in this case, resembling the real-life interactions between flora and fauna and this looming agent of light or ALAN. Now as I've highlighted before, because of both time constraints and processing power it was important to choose a system that illuminated the complexity of light pollution systems, whilst maintaining something feasible to model. Ok, so I've coined my model the "Orb-Web spider ecosystem" and it works like this: orb-web spiders, their insect prey, the prey's diet of grasses and finally lights are the agents within my model. Now, as recent studies have found, orb-web spiders are negatively impacted by the influx of night lighting, as they typically reside in the backyards, fences, walls and gardens that can support their intricate web designs. This intersection of ecosystem dynamics, emblematic in the orb-weaver spiders' natural lifestyle and social dynamics, the urban neighborhoods it often inhabits intrigued me as it would offer a level of complexity that paralleled the light pollution problem. Now as for the interactions between these agents, I limited them to growth and fecundity rates estimated for the spiders and their insect prey and the growth rate of the grasses, coupled with the basic food web dynamics of the system, or that the spiders eat the prey and the prey the grasses. With the addition of light, which were 18 in number given the average distribution of lights for an urban neighborhood, I added disruptor functions that changed the growth, fecundity among other properties of the insects and prey once within a certain diameter of the light. I visualized this model in a python library known as Mesa which is used for agent-based modeling and got the following results.

4.1 Agents

Pictured below is a snippet of the code in which I defined classes of spiders, insects, grasses and lights with their given properties and interactions between one another in a 2-d environment, much like the one in the late James Conway's game of life. In the code snippet, I define solely the spider agent.

```
class Spider(Agent):
def __init__(self, unique_id, model, age, fecundity, growth):
    super().__init__(unique_id, model)
    self.age = age
    self.satiation = 100
    self.fecundity = fecundity
    # self.grid = mesa.space.MultiGrid(width, height, True)
    self.growth_rate = growth
```

In the visualization, populations of lights, spiders, prey and grasses fluctuate. Dark green agents are spiders, yellow agents are of course lights, lime green agents are grasses and finally blue agents are the insect prey.

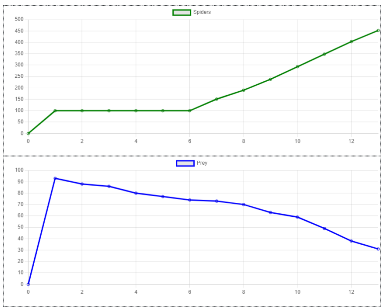

Figure 3: Spider-Insect population graph outputted by Mesa

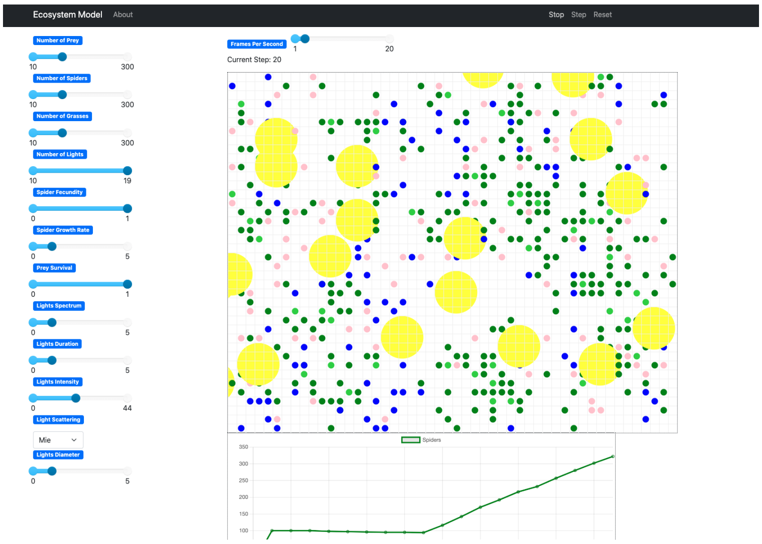

Figure 4: The Mesa Model GUI

Yet, to truly capture the properties and their relation to real-world phenomena, the aforementioned network theory held the answer. So how do we translate the Orb-web spider system into a network? The process is underscored by the topology of a network. Networks or graphs are defined as a set of nodes or vertices as they label them in this picture, connected by lines or edges. In a more holistic sense, the objects or agents within a system are nodes, and the links or the information that connects these nodes together are visualized as these links or edges. Now by exploring the topology of networks, we can uncover the underlying behaviors and properties of a system, so accordingly I translated my agent-based model into a network, in which the agents, like the spiders, grasses, lights and prey were the nodes and the edges were the interactions between them in their socio-ecological environment. I used the python library networkx to render this translation and ouputted a figure like the following, with randomly assigned values for parameters:

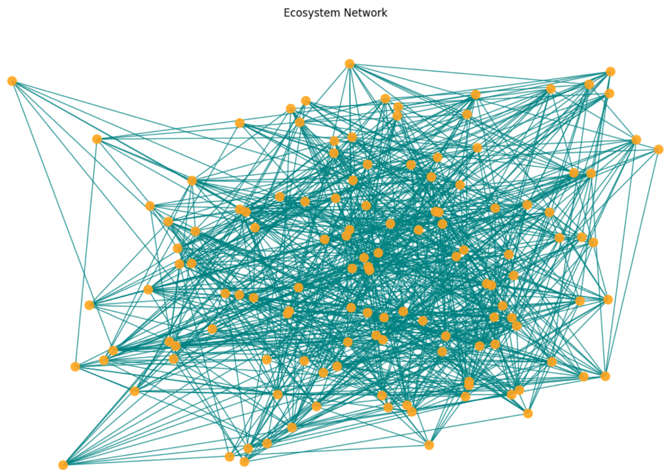

Figure 5: Network visualization of the ABM model

4.2 Verification

The verification of this model lies in observed interactions of spiders, light, insects and grasses across a multitude of sources and empirical data collected by researchers. However in the future I hope to create a more robust method of calibration and validation for my model. Yet, ultimately I was content in my decision to direct my focus towards the analysis of the model. After all, agent based models simply aren't capable of perfectly matching empirical data at the micro-level but rather responding to certain variables within that system most important to the modeller. Thus I employed face validation to verify my model against the conceptual 'Orb-Weaving Spider Ecosystem'. In tandem with face validation, however, there was one metric I used to test for statistical significance of the outputted data from my agent based models, or p-values of greater than 0.05. For my data I received the value of 0.0015689 which is less than 0.05 using the available functions under the SciPy library.

5 Methods and Results

In our given network, 4 parameters of the light agent/node are changed. These parameters are shown in table 1.

Table 1: Parameters

Parameter	**Description**
Spectrum	Spectral composition of light
Duration	The length of illumination periods during the nighttime
Intensity	How much light is there in lux/-candela?
Scattering	Reflected through aerosols and is 'scattered' throughout the sky

These parameters are defined by the following characteristics. Spectrum is an adjustable parameter, with a range of 320 nm to 1100 nm , since halogen lights which are typically used in city lighting are in this spectral range. Duration is simply a time spectrum parameter, where time (sec) is also adjustable. Intensity is another adjustable parameter that takes lux of light as an argument. Finally scattering is an adjustable parameter that gives the options of Rayleigh and Mie scattering. It occurs when the diameter of a particle interacting with photons is less than 50nm, or (where P is particle diameter) $P < \frac{1}{10}\lambda$. Mie scattering on the other hand occurs when interacting particles have diameters that occupy the range between 50-500nm, or follow: $\frac{1}{10}\lambda \leq P \leq \lambda$. Mie scattering of photons becomes more directional and is scattered forward, additionally, less light is scattered to the sides. Mie Scattering is described by the following equations: Q_s is proportional to:

$$x = (\frac{r}{\lambda})^4 \tag{1}$$

$$Q_s = \frac{\sigma_s}{\pi r^2} \tag{2}$$

Rayleigh scattering on the other hand follows the following equations:

$$Q_s = \frac{\sigma_s}{\pi r^2}$$

$$\left(\frac{r}{\lambda}\right)^4$$

Figure 6: Rayleigh Scattering

Where λ is wavelength and Q_s is proportional to

$$(\frac{r}{\lambda})^4$$

. Rayleigh scattering of photons on the other hand follows a peanut shaped distribution. The distributions of both are shown below:

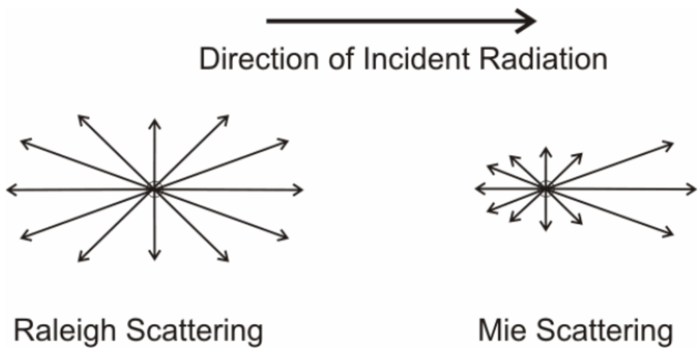

Figure 7: Rayleigh v Mie Scattering

I accordingly implemented this feature, in both the agent-based model and network representation of the system, where users can toggle between Mie and Rayleigh scattering in the system.

Thus adjustable parameters of the model include, spectrum, duration and intensity. These parameters thus act as independent variables, and by adjusting parameters allow us to view the behavior of the system under different light conditions, and thus offer recommendations and updates to current policy regarding urban light usage.

The question naturally becomes, how do we characterize behavior of our system?

The metric depends on three factors, resilience, stability and regime shifts. These metrics are the expected emergent behaviors of our given system. Through analyzing network topology and outputted data from the agent based model, such emergences are quantified and sufficiently characterize the positive and negative behavior of the model, which emerge under different parameter settings.

5.1 Resilience

I define system resilience as the property of a system to recover from perturbation or disruption. Similarly, if I target a system, how well will it hold from the attack. My definition emulates the one established in 1973, by CS Holling or that, "resilience is the ability of ecosystems to eliminate the impacts of external disturbances and maintain stability through their own repair." In biological and ecological networks, like the one I was analyzing, is often characterized by structural stability of the network. Thus I could analyze my network's topology to assess it's resilience. Thus, I implemented a edge attack algorithm, that visualizes the cascading and recovering impact of a perturbation or disruption to a connection between nodes or agents in the system. The algorithm works, by first selecting random edges to attack (delete) and subsequently deleting the edges with node degrees, or connections to other nodes in the graph,less than 2. The algorithm is depicted below:

Algorithm 1 Network attack algorithm

Require: :Remove Edge G
  while $N \neq 0$ **do**
    if $D \leq 2$ **then**
      remove edge
    else if $N == neighbor$ **then**
      remove edge
      add edge if it becomes isolated to N
    end if
  end while

After the algorithm terminates, I analyzed the topology of the network to assess its resilience. This was done by searching for the largest connected component in the network. Implemented through the built in networkx function, connected_components. Networks with larger connected components, or number of connected nodes in a partition of a network were valued as having higher resilience. These connected components would look like the figure below:

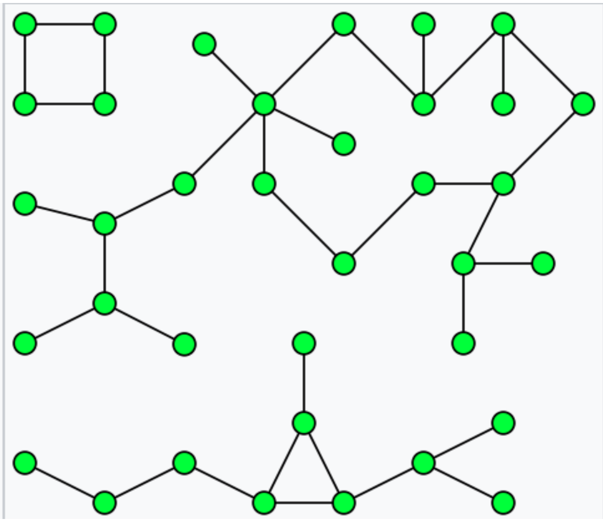

Figure 8: Connected Components

5.2 Stability

The structural stability of our ecological network is furthered by an additional factor, stability. Stability places structural resilience in a biological perspective, by studying the strength of an ecosystem in the face of adversity. The study of stability is rooted in zoologist, Charles Elton's stability-diversity hypothesis, that in ecological systems, biodiversity enhances stability of an ecological system. While recently met with revisions to consider the complexity of systems that contribute to stability, it is accepted that biodiversity is positively correlated with stability of an ecosystem. Thus, we can use biodiversity as an implicit metric for the stability of an ecosystem. Biodiversity is calculated through a metric known as Simpson's diversity index. The equation for the Simpson's diversity index is as follows: 1 minus the sum of the number of individuals within a group times the number of individuals minus 1 quantity over the total population times the total population minus 1. Or as summarized equation below:

$$D = 1 - \frac{\sum n(n-1)}{N(N-1)} \tag{3}$$

Biodiversity is calculated for every network iteration with adjusted parameters, by summing the number of grass nodes, spider nodes and prey nodes.

This biodiversity calculation is completed through a python function to calculate the Simpson diversity index. Biodiversity is then compared against topological features of the networks like modularity, eigenvector centrality, connectivity, closeness and betweenness centrality to test for correlation to biodiversity. This correlation was assessed by a metric known as one-way ANOVA, which measures for statistical difference between two groups.In addition, my process also used the f-statistic and p-values acquired from the variance analysis of ANOVA to measure statistical significance and correlation between two variables. This preliminary step is necessary, as their is ambiguity in scholarship around the general connection of network features and stability. Thus it was imperative that I ran my own assessments to determine the best topological metrics for stability All five of the topological features were easily implementable through the networkX library, as they were built in. Features that showed positive correlation (via finding Pearson correlation coefficients) to biodiversity were thus considered in assessing networks stability. Ultimately, the features that were chosen for highest correlation were used to assess the stability of the parametrically distinct systems. Those with higher values for a given topological feature would correlate to a higher level of stability. These features I identified were modularity, eigenvector centrality and connectivity.

Additionally, another metric was or the presence of communities. In a similar vein to the biodiversity and topological feature approach, this metric saw perturbations in the form of distinct values of parameters for light, spectrum, intensity, duration and scattering. The presence of communities suggest higher stability within a system. The implementation of this approach, I scoured through popular community detection algorithms and decided upon the Girvan-Newmann algorithm, which removes edges to identify the tightly-knit communities underlying the network. More of these communities suggested more stability.

5.3 Regime Shifts

The final metric considered in my analysis, was the quantification of regime shifts. The idea of regime shifts is classical to most ecological research and describes the change in behavior of an ecological system, or the shift of ecosystems to different states. Catalysts to such transitions are called tipping points, or as I translated them in my analysis, change points. These change points anticipate the shift of ecosystem behavior over time and thus, I had to review the time series data outputted by my mesa model, where agent population was graphed against time, like the ones outputted in figure 3. I downloaded my data into a pandas dataframe and then into a csv, ready to be analyzed by a change point detection algorithm. My algorithm depended upon the ruptures python library. My algorithm implements a Reproducing Kernel Hilbert Space (RKHS) process that works by replotting my graphs to the high-dimensional vector space. My approach identifies change points through three available kernel functions in the rupture library, Linear, RBF and Cosine. This works as an optimization problem which segments the data based on the change points. At these change points, I used numerical differentiation to calculate the derivative at each of these change points. The proportion of negative to positive derivatives was calculated for each network.

6 Results

Both the ABM and network representations for my model were run 17 times,to explore the parameter space of the 4 independent variables I was looking at, spectrum, duration, intensity and scattering of light. To choose the sampled points of each parameter I employed simple random sampling to sample the parameter. For instance, to sample the duration parameter space I got a result like the following:

```
Simple random sampling of 5 numbers are:  [0, 6, 8, 3, 11]
```

Figure 9: Output Sampling

6.1 Stability

I identified the features most closely correlated with biodiversity as eigenvector centrality, modularity, and closeness centrality of a network. Biodiversity was calculated through the following python function:

```
import pandas as pd
data = pd.read_csv('data.csv')
species_counts = data.sum().to_dict()
print(species_counts)
def simpson_di(data):
```

```
    """ Calculate the Simpson Diversity Index from a dictionary of species counts.
    """
    N = sum(data.values())  # Total number of organisms
    if N == 0:
        return 0  # Prevent division by zero
    return sum((n / N) ** 2 for n in data.values() if n != 0)
diversity_index = simpson_di(species_counts)
# Print the result
print("Simpson Diversity Index:", diversity_index)
```

In which data.csv was the stored csv file of the output of my Mesa model's data collector for populations of spiders, grasses and prey. The python code outputted a result for a diversity index between 0 to 1. Which in the case of a run of my model to investigate the properties of a scenario in which lights had wavelengths of 707nm, or were approximately red in color I received the following result:

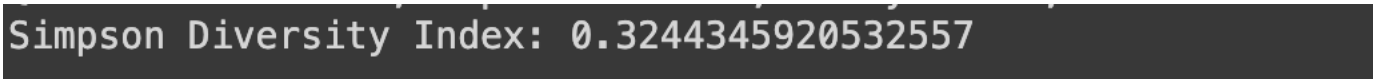

Figure 10: Simpson's Diversity Index

To analyze the topological features of the network representation of my model, I simply implemented built-in functions of the NetworkX library, and plotted my results. In the case of a scenario in which photons were scattered via Rayleigh Scattering, I gathered the following outputs

The final correlated topological property of a network, modularity, or the density of connections within communities or modules of a network was written within a community detection algorithm. My algorithm graphed the modularity, calculated through a NetworkX function for each k-component or connected sub-graph within the network. For a source of ALAN that lasted 9 hours or epochs a day, the corresponding network produced the following modularity graph for each k-component:

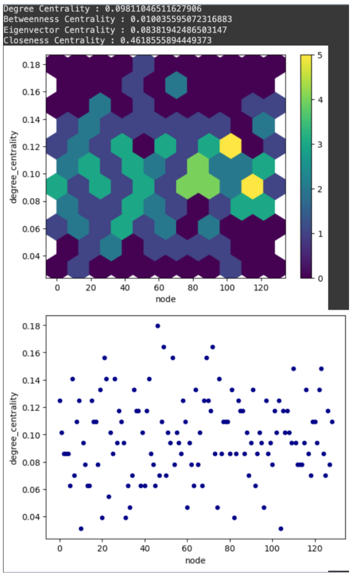

Figure 11: Eigenvector Centrality

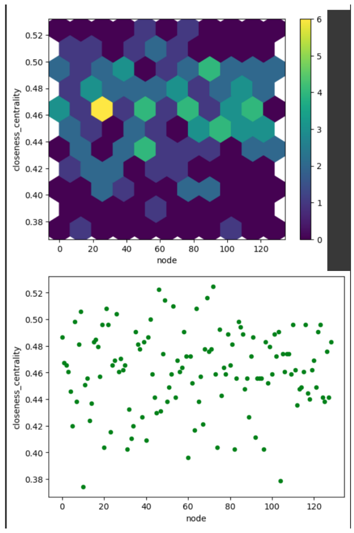

Figure 12: Closeness Centrality

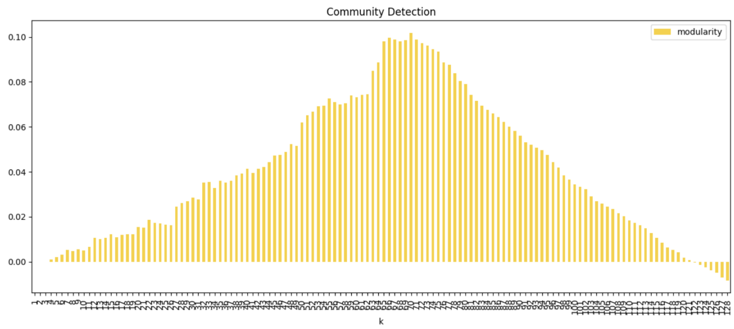

Figure 13: Modularity Graph

Such relevant topological features as proven by ANOVA f-statistics, calculated through available functions in python's SciPy library, shown below, like eigenvector centrality, modularity and closeness centrality were calculated for each set of sampled points within the four parameter spaces.

```
F_onewayResult(statistic=1019962.9761778761, pvalue=5.7673
9367391355e-12)
F_onewayResult(statistic=2138025.5871308297, pvalue=1.3125
74913031973e-12)
F_onewayResult(statistic=1087.5625732486135, pvalue=5.0417
95602583616e-06)
F_onewayResult(statistic=1306549.535457872, pvalue=3.51477
2944325627e-12)
F_onewayResult(statistic=11440.213595081788, pvalue=4.5817
34781990638e-08)
```

Figure 14: One-way ANOVA p-values and f-statistics for 5 topological features, Eigenvector Centrality, Modularity, Betweenness Centrality, Closeness and Degree Centrality

Since higher f-statistics indicate higher correlation between two variables, Eigenvector Centrality, Modularity and Closeness were chosen as the most indicative metrics of biodiversity and thus stability.

Some loose trends emerged, the aggregated eigenvector centrality of networks with variable light spectra, bore interesting results. For example, cooler lights or lights with wavelengths between 400 and 600, or violet to light green had the highest eigenvector centrality, of 0.8522 an 0.8546 respectively. Eigenvector centrality refers to nodes with the most influence over other nodes within their network, this may characterize the significant impact of warm colors on ecosystems. This was countered by a general trend, warmer lights contribute to greater stability within an ecosystem, as the aggregated score of modularity, eigenvector centrality and closeness centrality was higher with warmer colors between the spectrum of 650 to 750nm or deep orange to red, with aggregated scores almost 0.2 greater than their cooler color counterparts. Furthermore, 3 hours of ALAN usage proved the most network stabilizing, as it consistently ranked highest through the aforementioned topological features, and earned an aggregated score of 0.1894116, the highest of any of the changed variables for duration. For intensity, 20 lux proved the most stabilizing with an aggregated score of 0.4343086667, the highest of any of the changed variables. In scattering, Mie scattering was more stabilizing with an aggregated score of 0.1822181333. This outcome is consistent with our other findings, since Mie scattering often prefers or occurs with photons of longer wavelengths, or warmer colors on the light spectrum.

Additionally, other metrics were used to analyze the stability of our given network. The process was initialize through built-in functions of NetworkX like community detection algorithms. To commence my analysis I use one such built-in function, that identified communities through the Girvan- Newmann algorithm. The code for the aforementioned steps is below:

```
G = model.G
communities = list(nx.community.girvan_newman(G))
print(communities)
```

This code in tandem with visualization libraries and the discovery of modularity for individual nodes or agents in a system resulted in results like the following (specifically for 707nm wavelength of light):

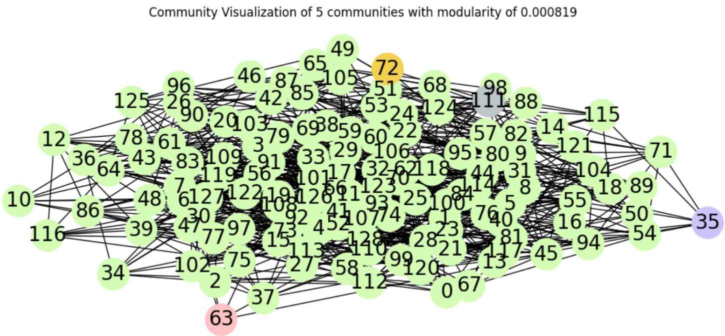

Figure 15: Communities Graph, note colors signify different communities. In this image there are 5 colors corresponding to 5 identified communities

My code also allowed me to look at the largest connected component in the network of the socio-ecological system, as well as the degree, or how many edges branched off from a node in the network in the images below:

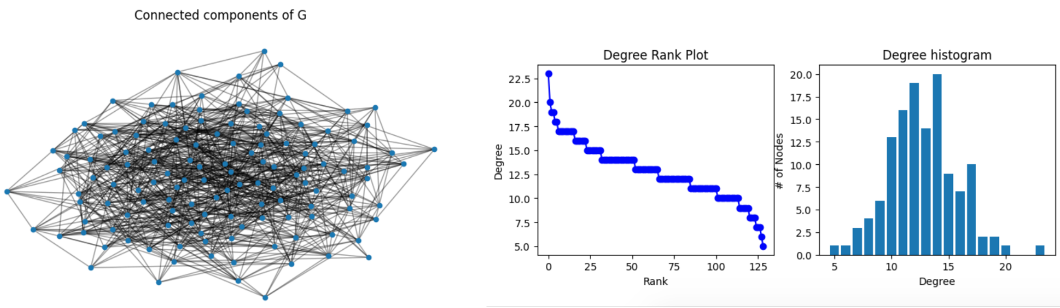

Figure 16: Topological structure

Both degree centrality and connected components are good metrics of stability, because they reveal the graphs and by relation, the system's ability to tend towards becoming a k-connected graph, in which removing edges from the network never disconnects the network.

Communities were most prevalent at certain conditions within the investigated parameter space. For example, scenarios with high modularity resulted in a greater number of communities. This logic is consistent, as modularity measures the degree to which a network can be partitioned or separated. This logic follows S.Gomez and P.Jensen's Balance Theory which states the following, where Q_E^- and Q_E^+ refer to the negative and positive edges that may separate communities. Negative edges form out of severed relationships, like the prey and the spider, and ultimately particular settings of light and the organisms within the system. Positive edges on the other hand form from positive relationships between organisms in this case:

$$Q_E = \frac{2\omega^+}{2\omega^+ + 2\omega^-} Q_E^+ + \frac{2\omega^-}{2\omega^+ + 2\omega^-} Q_E^-,$$

$$Q_E^+ = \frac{1}{2\omega^+} \sum_i \sum_{j(i \neq j)} \left(\omega_{ij}^+ - \frac{\omega_i^+ \omega_j^+}{2\omega^+} \right) \delta\left(C_i, C_j\right),$$

$$Q_E^- = \frac{1}{2\omega^-} \sum_i \sum_{j(i \neq j)} \left(\omega_{ij}^- - \frac{\omega_i^- \omega_j^-}{2\omega^-} \right) \left(1 - \delta\left(C_i, C_j\right)\right),$$

Figure 17: Balance Theory

For spectrum the highest number of communities was discovered for lights with wavelengths of 686 nm. For intensity, the setting of the lights with 20 lux produced the greatest number of communities, for duration 3 hrs of ALAN usage once again prevailed amongst the other parameter settings and held the highest number of communities. Mie scattering triumphed over Rayleigh scattering for the greatest number of communities.

6.2 Resilience

The analysis and emergence of stability in a network offered insight into the properties of the ecosystem, by associating topological features with observed properties of the system, like biodiversity or population statistics. Resilience, conversely, quantifies properties of the representative network of an ecosystem, yet still lends much insight into the structural robustness of our system. Thus I employed the previously defined node attack algorithm to measure the structural resilience of a network. Using a python algorithm to attack nodes, for a scenario in which the intensity of lights was 33 lux, I uncovered the following result or output from my algorithm. The largest connected component was subsequently outputted afterwards.

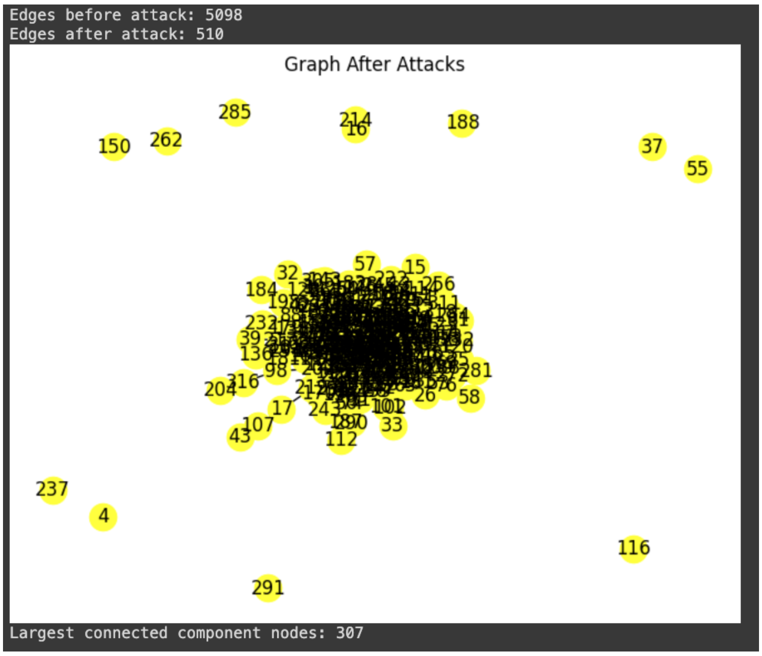

Figure 18: Graph after node attack

Additionally I ran the algorithm multiple times as an additional metric of measuring how long a network could withstand the node attack algorithm. The second and third runs of the node attack algorithm on the network with light intensities of 33 lux are shown below:

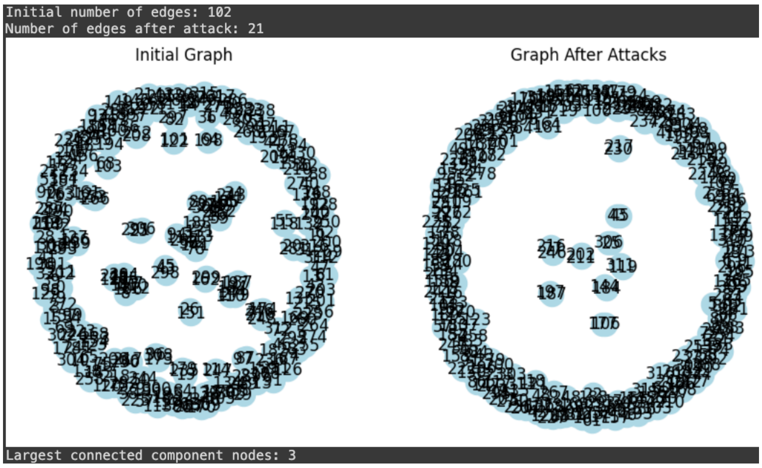

Figure 19: Graph after multiple node attacks

Resilience was ultimately assessed by the number of connected components, still intact after the node attack algorithm had affected a network once. Unfortunately there weren't any clear patterns that emerged from the largest connected component analysis, which opens up further questions on the disjointed relationship of structural resilience to outwardly expressed properties of systems like stability and regime shifts, or a slight error in my code that might shield such results. As shown in the graph below, the values for largest connected component for each value of stayed level across the parameter range of light intensity, and bears only a slight resemblance to a parabolic curve.:

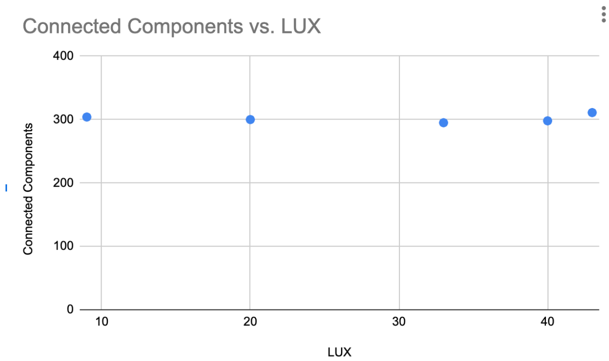

Figure 20: Exceptions

Similar relationships were identified for the rest of the three independent variables.

6.3 Regime Shifts

Regime Shifts, the final component to my analysis, partition the data outputted by the Agent-base model by change points, or slight shifts in the state and behavior of populations of, in this case, spiders, prey and grasses. I used three kernels and ultimately identified the cosine kernel as the overwhelmingly worst kernel to identify such change points. The Linear and RBF kernels were much better at doing so, as exemplified by the change point detection algorithm output on a scenario with lights wavelengths of 414nm:

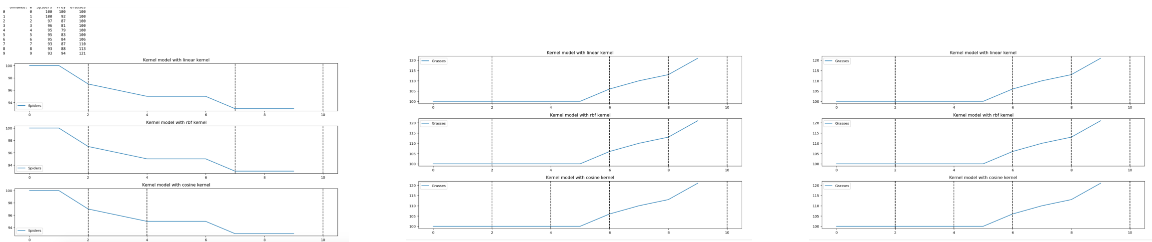

Figure 21: Kernels change point detection for spiders, prey and grasses

Regime shifts, after identified through change point detection were thus classified as either positive or negative change, by simply calculating the derivative of the change point through a simple python implemented numerical differentiation algorithm below which takes a dictionary of points uploaded from my data.csv file:

```
    h = x[1] - x[0]  # Increment between adjacent x values
derivative_at_index = (y[index + 1] - y[index]) / h
print("The derivative at index", index, "is approximately:", derivative_at_index)
if derivative_at_index > 0:
  print("positive change")
else:
  print("negative change")
```

The results approximately followed those observed in the stability section, with the most positive change at a wavelength of 686 nm for the spectrum parameter with an overall derivative of 1.357, at 9 lux for the light intensity parameter with an overall derivative of 1.245, at 3 hours for the duration parameter with an overall derivative of 1.578 and finally Mie scattering prevailed once again over Rayleigh scattering with an overall derivative of 1.286. Additionally, as I outputted 3 kernel functions to approximate the change points, on average the RBF and Linear kernel functions approximated the change points more accurately, but there were some exceptions. For example, for the scenario in which ALAN lights had a wavelength of 591 nm, the Cosine kernel function proved one of the better approximations:

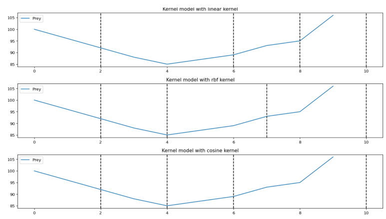

Figure 22: Cosine Kernel Function for Prey

7 Policy

7.1 Existing Policy

Policy on ALAN is quite variable throughout the contiguous United States, and becomes even more pronounced throughout the world. Thus, for the scope of my project, I analyzed the current in place policies in New Mexico, USA.

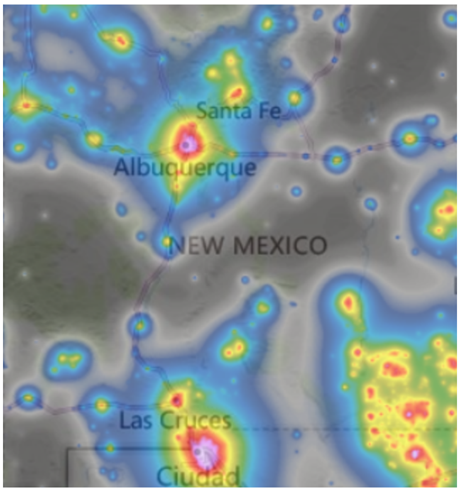

Figure 23: New Mexico ALAN map

The Dark Skies Conservation Trust of Santa Fe instituted the Night Sky Protection Act in 1999, which, a novelty for it's time, "makes dark skies a priority in New Mexico for the health of its people, wildlife, and economy. The act requires that outdoor lighting be fitted with shielding that directs light downward, rather than upward or laterally." This light positioning ensures the view of a partially or fully visible night sky, however its effects on biological systems have not been thoroughly investigated and advised. As Ed Yong, a science writer for the Atlantic summarizes in his novel, *An Immense World*, "The daily and seasonal rhythms of bright and dark remained inviolate throughout all of revolutionary time–a 4-billion-year streak that has began to falter in the 19th century." Artificial lighting thus proves a threat to the 'sensory-scapes' of a great variety of species, in addition to obscuring our view of the night sky. Position of lights is thus not as important to the condition of an ecosystem, but rather properties of light like spectrum,duration,intensity and scattering are more crucial to consider. In the New Mexico House Bill 461 of 2009, 10 years after the Dark Skies Conservation Trust instituted their efforts, made slight revisions to the outdoor lighting policies in New Mexico. Most notably was a sole mention of intensity of light provisions as stated below:

light source of sixty-five watts or greater or a light source with an intensity exceeding a maximum light output of seven hundred fifty-five lumens produced by the light source shall:

Figure 24: Bill 461

Thus my recommendations lie in reassessing this statement as well as adding potential updates to the house bill based on my findings above.

7.2 Recommendations

Note: While I have results, before the expo, I want to ensure the accuracy of my data before adapting the House Bill 461 to better suit my findings, however I know that adding provisions to change to warmer colors and accordingly, larger wavelengths of light is imperative, as well as decreasing duration to around 3 to 6 hrs a day of light, and keeping intensity at around 9 to 30 lux is preferable for the health and success of surrounding ecosystems and natural habitats.

8 Conclusion

The central question of my research calls for awareness around light pollution. The answer lies in policy. Policy and law after all is our best measure to enforce rules and influence the public. As Steve Kaisler at the university of Notre Dame explains, "The nature of complex systems can be assessed by investigating how changes in one part affect the others, and the behavior of the whole." Thus by making minor changes to the light agent, I hope to explore and compare the emergent behavior of these different networks to inform infrastructural and social policy. Ultimately at the heart of my process is the use of science for the embetterment of the world, this same sentiment is what drives others in the scientific field, and the other systems of people and organisms in the world. It is the emergent behavior to do good that unites us, and to recognize the unsung systems around us.

9 Achievements

My greatest achievement was learning how to use both the NetworkX python library and the MESA agent-based modeling library as well as exploring systems and network analysis and how they could be interpreted in a biological framework.

10 Acknowledgments

I'd like to thank my sponsoring teachers Ms.Jocelyne Comstock, Ms.Gabriella Masoni for providing the space for me to work and help from Dr.Mark Galassi on this project.

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