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. 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

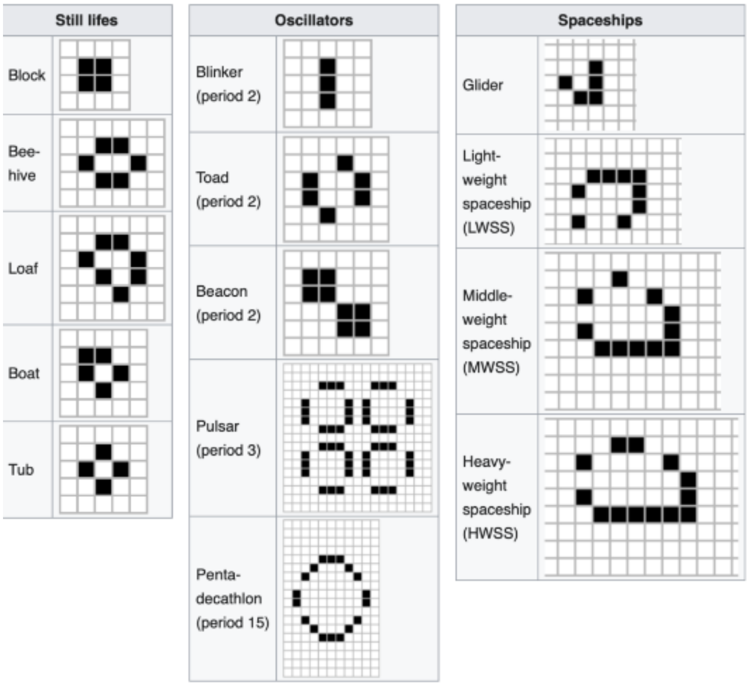

Figure 2: Conway's game of life emergent behaviors

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.

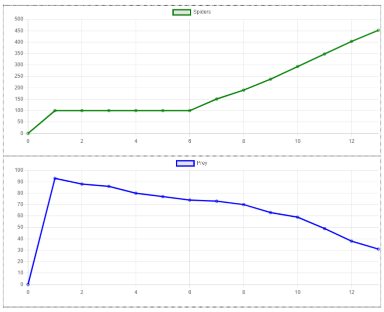

Figure 3: Spider-Insect population graph outputted by Mesa

```
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.

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:

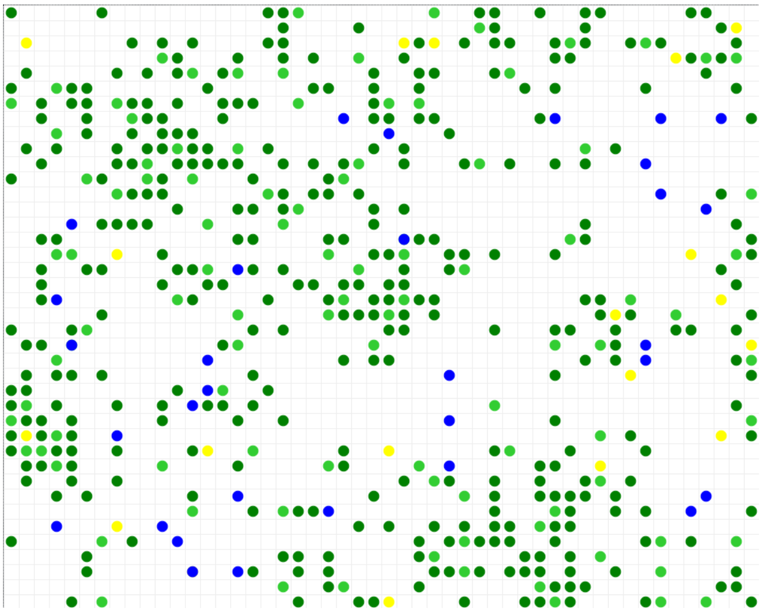

Figure 4: Output

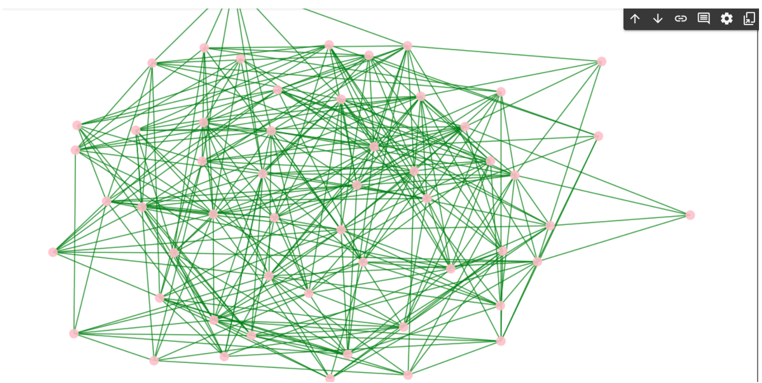

Figure 5: Network visualization of the ABM model

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'.

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

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

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

Figure 6: Rayleigh Scattering

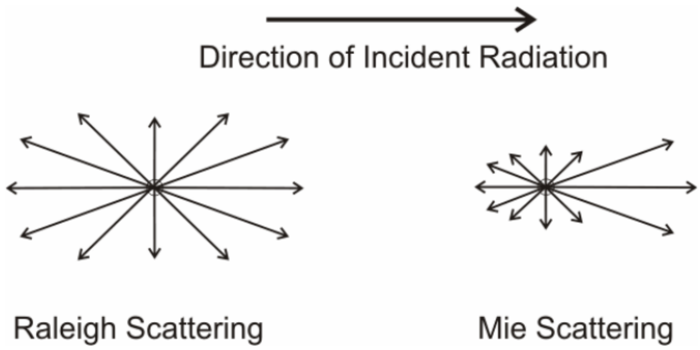

Figure 7: Rayleigh v Mie Scattering

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:

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

Unfortunately however, at this time, the adjustable parameter of Mie and Rayleigh scattering hasn't been successful in trial runs. By the Expo, and after some debugging, however this feature will be available.

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. Through analyzing network topology and outputted data from the agent based model, these factors 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:

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:

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

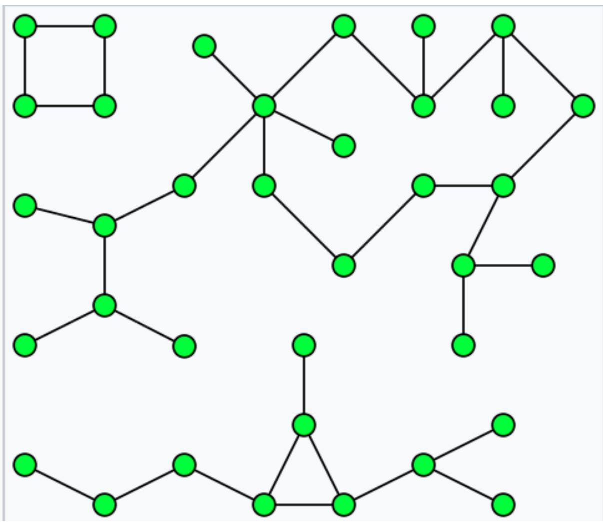

Figure 8: Connected Components

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 the ecopy python library that has a built-in function for the Simpson diversity index. Biodiversity is then compared against topological features of the networks like modularity, eigenvector centrality, connectivity, closeness and betweenness centrality (see appendix for definitions) to test for correlation to biodiversity. 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 Kendall 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 Note about Results and figures

You can find the necessary figures and results on the Readme on my github repository for this project: https://github.com/Dirac12/Orb-Web-ALAN-Ecosystem

7 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. By the Expo, I should have these policy regulations uploaded. 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.

8 Achievements

My greatest achievement was learning how to use the NetworkX python library.

9 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.