Protecting the Duke Forest – Developing an Assessment of Threats, Vulnerabilities, and Risks to Forest Resources and Management Priorities

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GC Focus: Restore and Improve Urban Infrastructure
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Abstract

This study develops an approach that can be used by the Duke Forest management team in order to protect the forest from impacts due to climate change and invasive species as well as to achieve their goals related to growth. To assist the Duke Forest in achieving these goals, an objectives hierarchy and influence diagrams were created to elicit the contributing factors to the Forest’s goals and assess each goal for threats and vulnerabilities. A preliminary analytical model was then created to evaluate future timber revenue, which serves as an example of how the qualitative risk assessment models can be quantified to generate probabilistic predictions of ecosystem responses to alternative management strategies. It was found that timber revenue will likely decrease significantly due to the impacts from climate change. However, other factors for growing pine trees should still be evaluated such as the revenue that can be generated from carbon credits, which can still help maintain revenue currently generated from timber. By developing the analytical model for timber revenue, it was shown that this approach can have broad applications in that it can be used to quantify the other influence diagrams created. By applying this method to the other objectives of the Duke Forest, one can create analytical and reliable models for decision analysis. Overall, by creating the foundation of a multiscale approach to evaluate decisions and to assess risks, this study can have strong potential benefits to the Duke Forest as well as to other forest systems.
1. Research Rationale

According to NAE Grand Challenges for Engineers, “Infrastructure is the combination of fundamental systems that support a community, region, or country. A major grand challenge for infrastructure engineering will be not only to devise new approaches and methods, but to communicate their value and worthiness to society at large.” The impacts of urbanization have affected numerous aspects of society through increased greenhouse gas emissions, population growth, and introduction of invasive species (Bombin & Reed, 2016; Li & Lin, 2015). These impacts in combination with growing pressure for infrastructure investment and resource extraction has posed great threats to forests by increasing the risk of land fragmentation and resource depletion (Bebbington et. al, 2018).

The importance of protecting forests, especially in growing urban communities, cannot be underestimated. We depend on forests for our survival as they provide habitats for animals which helps maintain biodiversity. In addition, forests provide wood, cleaner air, watershed protection, and soil erosion prevention (The Importance of Forests, n.d.). They also play a strong role in urban communities, as forests are used as a place for research and recreation (Childs, 2016). Therefore, there is a need to protect forests, an important infrastructure component in communities, from the growing threats of urbanization.

A prime example of a forest experiencing the negative impacts of urbanization is the Duke Forest located in Durham, NC - a city with an annual growth rate of over 2% (Durham, North Carolina Population, 2019). In order to protect the forest, a modelling study is conducted to assess the threats, vulnerabilities and risks to forest resources and management priorities. Through quantitative and qualitative analyses, the goal of this study is to create models that can be used to protect Duke Forest from urbanization-related impacts like climate change and resource depletion, assist the management team in achieving their goals to grow the role of forest in the local community and as a research forest, and allow the forest to coexist with the growing, local community. Furthermore, it is a priority for the results to have broader applications, so that the models created can be adapted to support other forests.
2. Introduction

2.1 Background to the Duke Forest

The Duke Forest, as we know today, has its origins in the mid-1920s, when the University administration purchased many small farms and interspersed forest as land for the new campus, as a buffer area, and as an investment for the future (Durden, 1993). Today, the Forest consists of approximately 7,052 acres of land, lying primarily in Durham and Orange Counties (Childs, 2004).

In 1931, Duke Forest was placed under intensive management by Dr. Clarence Korstian, its first director (Childs, 2004). In the Forest’s early development, several basic objectives were emphasized. These included timber management techniques on a practical and economical basis, development of an experimental forest for research in the sciences associated with timber growing and development of the area as an outdoor laboratory for students (Korstian and Maughan, 1931).

Modification of these early objectives has arisen, in part, through a greatly increased interest and dependence on the Forest for research in other areas such as environmental sciences and zoology. Research on current problems, many associated with global climate change and human impacts on the environment, has increased the Forest’s value as a research facility (Childs, 2004). Through the years the Duke Forest has provided many research projects with valuable data. For example, studies involving plantation spacing, microclimatology, population dynamics and forest succession have contributed significantly to the forestry sciences. In addition to supporting education and research at local universities and schools, the Forest participates in community outreach through tours and other events (Childs, 2016).

As the role of the Duke Forest has expanded since 1931, so have its overarching goals. According to the Duke Forest 2017 5-Year Strategic Plan, the management priorities today include (1) promoting the teaching and research mission by facilitating a diverse array of projects and programs, (2) sustainably managing resources for timber production, forest health, water quality, and wildlife habitat, (3) protecting rare species, unique ecosystems, historical sites, and archaeological resources, (4) providing education and outreach opportunities about natural resources and forest management, and (5) offering recreational and aesthetic amenities to the community. In an effort to achieve these goals, Duke Forest wants to build a management plan that considers and is responsive to present and future threats to management priorities (Childs, 2016).

2.2. Risk Modelling

Often, decision-making in environmental management is a difficult process, as one needs to provide a predictive link between actions and responses (Jorgensen, 1995; Clark, 2001). In particular, the lack of tools for forecasting economic, social and environmental value as a function of environmental management intervention has presented a challenge to forest decision-makers who must assess the impacts of monetary investments and sustainability practices on a variety of uncertain future benefits (Muthoo, n.d.).
Proper decision making often requires some type of risk management technique. Risk management refers to the “to the practice of identifying potential risks in advance, analyzing them and taking precautionary steps to reduce/curb the risk.” (“Definition of Risk Management,” n.d.) A key component of risk management is determining appropriate content to ensure that the outcomes are reliable. Thus, effective risk management requires authoritative and trustworthy sources (Morgan, 2011). Furthermore, the information gathered from the sources must include effective communication, so that the risks inform a wide range of audiences in an appropriate and engaging manner (Lang, 2001).

To conduct a risk management analysis, one can use integrated models. Integrated models represent attempts to combine the information collected from numerous credible sources into a single framework (Pielke, 2001). However, since there is often a variety of scales at which sub-models occur, a challenge for modelers is to incorporate these smaller models into larger, coherent, and functional predictive models (Levin, 1992). To combine sub-models, representation at multiple scales and in a variety of forms is required (Borsuk, 2004). There is also a need to assess how uncertainties in each component of the model propagate to uncertainty in the final predictions (Reckhow, 1994). Furthermore, the final integrated model should have the ability to reflect advances in scientific information and policy requirements (Rutherford, 1987).

2.3. Application of Risk Modelling to Duke Forests

Integrating risk into long term forest management means applying the entire risk management process to decisions about forest ecosystems. Although this process is well established in general business economics and in insurance mathematics, it is relatively undeveloped in forestry (Hanewinkel, 2010). With the goal of supporting a general modeling framework for integrating risk and growth as quantitative measures into long term forest management, we develop a risk assessment for the Duke Forest in an effort to assist the management team in developing a plan that considers and is responsive to present and future threats to its sustainability goals.

Based on previous work from Borsuk et. al, we have determined influence diagrams (Pearl, 1988; Jensen, 1996) to be a promising method for conducting this risk assessment model. Influence diagrams utilize probabilistic, rather than deterministic, expressions to describe the relationships among variables. This is an essential characteristic of an integrative model if predictions are to be used to guide decision-making (Clark, 2001). Furthermore, influence diagrams have graphical structures, which distinctly represent cause-and-effect assumptions between system variables that may be obscured under other approaches. These cause-and-effect assumptions can be used to create a complex causal chain that links management actions to consequences. Each of these relationships can be quantified independently using an approach suitable for the type and scale of information available. The independent relationships can then be scaled and combined accordingly to create a holistic model with the ability to propagate the uncertainty of each component to determine uncertainty in the final predictions. In general, a key advantage of this approach is that probabilistic functions describing the relationships allow relationships to be represented without the full complexity, or information needs, of highly reductionist models (Borsuk, 2004).
To demonstrate the application of this approach, a qualitative risk assessment was first conducted to fully understand the components of and threats to the management and sustainability goals of Duke Forests. These assessments were represented as influence diagrams with information gathered through expert elicitation and Duke Forest data. An analytical model using Analytica software was developed for the Forest’s “maintaining timber revenue” management goal. This model was created through expert elicitation, Forest data and utilization of a collection of previously published sub-models. It overall serves as an example of how the qualitative risk assessment models can be quantified to generate probabilistic predictions of ecosystem responses to alternative management strategies.
3. Methods

3.1. Elicitation of Objectives Hierarchy

Identification of measurable objective variables that are meaningful to the Forest management was the first task of this modelling study. The intent was to establish attributes that would be used by the decision makers to evaluate the success of the 5-year Strategic Plan (Childs, 2016) and should therefore be predicted by the model (Borsuk, 2004). The elicitation of objective variables is extremely important as inadequate attention to this step can lead to incomplete or misguided analysis (Reckhow, 1994).

In order to organize the goals, an objectives hierarchy was created to group smaller objectives. To do this, a list of preliminary “objectives” was first brainstormed, primarily through the use of the 5-year Strategic Plan. Expert interviews with Sara Childs, Director of Duke Forests, were then conducted to build the fundamental objectives hierarchy. By asking questions like “what do you mean by that?” led to the discovery of many sub-objectives that further describe what is meant by the fundamental objectives in this particular context (Objectives Hierarchies, 2013).

A means-end diagram is a conceptual model that visually shows the relationship between means and at one end and fundamental objectives on the other, where the means help lead to the overall objective. It was useful for developing a conceptual understanding of the system, for helping to separate special interests (objectives) from positions (means) and for identifying potential evaluation criteria (Objectives Hierarchies, 2013). For example, a means-end diagram for the Forest’s “Diverse Sources of Revenue” fundamental objective would include sub-objectives such as “maximize external funding” and “maintain timber revenue,” but also means like “adequate supply of timber.” As “adequate supply of timber” is a step toward “maintain timber revenue,” it is defined as a means objective and, therefore, not included in the objectives hierarchy but will be included later in influence diagrams. In addition, as the means-end diagram had the end at “maintain timber revenue,” it was labeled as a sub-objective and is included in the objectives hierarchy. A key advantage of means-end diagrams is that they help people see that issues that are not fundamental or sub-objectives still have a place in the process. The Objectives Hierarchy produced from the means-end diagrams, expert interviews, and literature research is shown in Figure 1.

3.2. Qualitative Modeling through Influence Diagrams

If risk management techniques are to be reliable and effective, they must reflect expert understanding. Therefore, a key step in developing a risk management assessment is creating influence diagrams that summarize the relevant reliable information available (Morgan, 2012) The advantage of influence diagrams is that they focus on the relationship between action and knowledge, and so encourage examination of the options to actively manage an uncertain system and to conduct systematic studies on how information can support management (McAllister and Peterman 1992).

An influence diagram is a directed graph, with arrows or “influences” connecting related “nodes.” The kind of nodes vary in shape and can have differences in meanings. These are
summarized in Table 1 (What is an Influence Diagram?, 2019). An arrow between two nodes means that the node at the arrow’s tail exerts some “influence” on the node at the arrow’s head (Morgan, 2012). The dependence of variables on each other is described by conditional probabilities (Kuikka, 1999)

<table>
<thead>
<tr>
<th>Type of Node</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision Node</td>
<td>A <strong>decision</strong> is a variable that one (or one’s organization), as the decision maker, has the power to modify directly.</td>
</tr>
<tr>
<td>Chance Node</td>
<td>A <strong>chance node</strong> is an uncertain quantity, whose value are unknown due to incomplete information, and which, (unlike a decision), cannot be controlled directly.</td>
</tr>
<tr>
<td>Variable Node</td>
<td>A <strong>variable node</strong> is a deterministic function of the quantities it depends on.</td>
</tr>
<tr>
<td>Objective Node</td>
<td>An <strong>objective</strong> is the targeted measurement/goal that the decision maker is seeking to better understand. Usually, the decision maker is trying to find decisions to maximize (or minimize) the objective.</td>
</tr>
<tr>
<td>Constant Node</td>
<td>A <strong>constant</strong> is a known quantity, that does not change but may influence other nodes.</td>
</tr>
</tbody>
</table>

The process to create an influence diagram is often an iterative one. A full influence diagram, developed through multiple reliable sources, can be a daunting task, but has numerous advantages since pushing the analyses as far as possible helps to refine thinking about a risk (Morgan, 2012)

For this study, influence diagrams were constructed using the assembly method (Morgan, 2012). As influence diagrams are a set of linked factors, they can be assembled by listing relevant factors and then figuring out how they are related. For this study, a dry erase board was used to first list factors and then use arrows to see how they are related. The initial diagrams were produced using literature and preliminary expert interviews. Weekly consultations were then conducted with Sara Childs to refine the influence diagrams. In addition, other members of Duke Forests such as Jenna Schreiber, Assistant Director, were consulted to further refine the
diagrams. The influence diagrams in this study were created by sub-objective, in that each sub-objective had its own influence diagram (Fig. 2-8). The eventual goal is to combine the sub-objective influence diagrams to create influence diagrams per fundamental objective, as well as to quantify the influence diagrams in order to analytically evaluate the impacts of the different variables.

3.3. Model Implementation

In order to implement the model, first an influence diagram was created for Duke Forest’s “Maintaining Timber Revenue” objective. After the qualitative influence diagram was elicited, the model was quantified to develop an analytical model that can be used for predictions. This was done using Analytica Software.

For the development of the analytical model, three sources were utilized and scaled accordingly. First, for the impacts of climate change on forest economics, a study from Susaeta et. al (2014) was utilized. This study analyzed the impacts on loblolly pine in the southeastern United States, primarily focusing on different levels of productivity scenarios, disturbance risks and salvageable rates resulting from climate change. To model impacts of an invasive species, another study from Susaeta et. al (2016) was utilized. This study explored the economic impacts of a hypothetical arrival of a destructive ambrosia beetle that infests loblolly pine forests in the Southeastern United States. To do this, there was a focus on level of control for the pesticide as well as the impacts on net present value of the forest (NPV). Furthermore, both of these studies were conducted in relation to Southeastern U.S. forests, making them excellent sources since the Duke Forest is also a Southeastern U.S. Forest and this similarity in geographic location helps remove confounding factors.

These two studies from literature were combined to fit one scale and then adapted for the Duke Forest. As the resulting output for climate change was Land Economic Value (LEV) and the output for pesticides was NPV, it was important to model this on one scale. A combined scale was created that modeled the “proportional change” in revenue to estimate the impacts of both climate change and an invasive species. To do this, the proportional changes in NPV and LEV were calculated. This proportional change in revenue was then applied to the Duke Forest by applying Forest data for acres harvested, future goals and past revenue from harvests of pine.
4. Results

4.1. Objectives Hierarchy

Figure 1 shows the objectives hierarchy created for the Duke Forest, with the overall goal being effective management of Duke Forest. The fundamental objectives include “Diverse Sources of Revenue”, “Conservation of Natural Resources”, “Efficient HR”, “Research and Teaching Promotion”, and “Community Engagement.” Below each fundamental objective are sub-objectives necessary to achieve each fundamental objective goal. For example, to have an efficient HR, one must maximize the capacity of staff resources as well as the efficiency across task staff allocation.

Figure 1. Objectives Hierarchy for Effective Management of the Duke Forest

4.2. Influence Diagrams

In order to achieve each fundamental objective and the Duke Forest’s overall goal of effective management, influence diagrams were developed for the various sub-objectives. Figures 2-8 show influence diagrams for some of the sub-objectives. When these influence diagrams are converted to analytical models, they can be combined for the overall fundamental objectives and the influences of each sub-objective on each other can be modeled and analyzed.

Figure 2 shows the influence diagram for the sub-objective: “Maximize Engagement Focused on Science, Environment and Natural Resource Management.” As shown, the primary
drivers that can help maximize this objective are expanding outreach efforts to under-represented groups, focusing on virtual engagement, maintaining ongoing engagement and expanding focused engagement. Furthermore, each primary driver has its own secondary drivers. For example, ‘focused engagement’ is dependent on the number of tours per year, annual gathering registrants and number of volunteer events. In order to maximize this sub-objective, Duke Forest management will have important decisions to make, specifically surrounding budget and staff hours as well as the allocation of these resources.

Figure 3 shows the influence diagram for the sub-objective: “Maximize External Funding.” For this, the primary drivers were determined to be fundraising money, grant money, and sales of merchandise/rentals. In order to maximize this sub-objective, the Duke Forest will have to make decisions regarding the allocation of staff effort toward fundraising, grant writing and advertising. Furthermore, the management team will have to choose what and how many grants to apply for, the price of their goods and the supply of their goods at gift stores.

Figure 4 illustrates the influence diagram for the sub-objective: “Minimize Land-Based Fragmentation.” For this, the primary drivers are the acres that the Duke Forest acquires and the acres lost due infrastructure projects. To help achieve this sub-objective, some measures that Duke Forest can take are to be committed to purchasing new land, allocate more funding toward land purchases and participate actively in the design of local infrastructure projects to help maintain and potentially even expand forest area.

Figure 5 depicts the influence diagram for the sub-objective: “Maximize Learning for all Students.” As shown, to achieve this goal, the Duke Forest should work to increase learning opportunities for a variety of groups, including K-12, Undergraduate, Graduate, Lifelong and Underrepresented Students. Furthermore, the Duke Forest can work to increase learning with public/mixed audiences. To achieve this goal, the Duke Forest will need to make decisions regarding effort, staff hours, and budget. This goal is also dependent on other factors such as the availability of teachers and provided infrastructure, which might serve as limiting factors.

Figure 6 shows the influence diagram for the sub-objective: “Minimize Impacts from Invasive Species.” As depicted, there are many factors involved that are outside of the Duke Forest’s control such as changes in temperatures and weather patterns, international introductions and efficacy of control measures. Therefore, this leaves a lot of uncertainty for the Duke Forests, but they can potentially prepare for the risk of invasive species in ways such as emergency budgets, staff capacity, and application of control measures.

Figure 7 shows the influence diagram for the sub-objective: “Minimize Negative Impacts from Community Engagement.” As shown, the Duke Forest is currently experiencing multiple drivers of negative impacts from community engagement including litter, dogs, hunting, off-trail use, and unauthorized access points. To truly be able to minimize these negative impacts, the Duke Forest will have to make decisions related to signs, teaching efforts, budget and staff hours allocation. Furthermore, the achievement of this goal will be dependent on factors such as compliance with rules/regulations and availability of outside resources, which are components that the Duke Forest cannot necessarily control for. But with more outreach efforts and signs, the Forest has potential to be successful.
Figure 2. Influence Diagram for Sub-objective: Maximize Engagement Focused on Science, Environment and Natural Resource Management

Figure 3. Influence Diagram for Sub-objective: Maximize External Funding
Figure 4. Influence Diagram for Sub-objective: Minimize Land Based Fragmentation

Figure 5. Influence Diagram for Sub-objective: Maximize Learning for all Students
Figure 6. Influence Diagram for Sub-objective: Minimize Impacts from Invasive Species

Figure 7. Influence Diagram for Sub-objective: Minimize Negative Impacts from Community Engagement
4.3. Analytical Model and Regression Results

The primary purpose of influence diagrams is to eventually quantify the results in order to make predictions and mitigate risks. To illustrate this process and evaluate its potential for being applied to the Duke Forest, an analytical model was developed for the sub-objective: “Maintain Timber Revenue.” To do this, a qualitative model was first developed through an influence diagram as shown by Figure 8. As shown, there are multiple ‘chance’ nodes that lie outside of the Duke Forest control, such as disturbance events, market demand, and pest/disease invasion. To counter this uncertainty, the Duke Forest has the ability to make decisions surrounding intensity of management, responsibility of timber management and planting.

Figure 8. Influence Diagram for Sub-objective: Maintain Timber Revenue

To begin developing the analytical model, a few assumptions were made. First, it was assumed that the primary risks were due to climate change and pesticides. Therefore, these were included in the analytical model and then adapted to the Duke Forest. Second, the impacts of market access and prices were not included as these have many fluctuations which would increase error significantly. It was also assumed that the effects from climate change and pesticides would be more significant, and therefore should play a larger role in the model. Third, two studies from Susaeta et. al (2014, 2016) were utilized to develop models for the impacts from climate change and pest invasions. It was assumed that because these studies were
conducted on Southeastern U.S. Forests loblolly pine, they can be directly applied to the Duke Forest for their pine pulpwood revenue.

Figure 9 shows the analytical diagram created in order to evaluate the impacts of climate change and pest invasions on timber revenue. As depicted, the Duke Forest can make decisions regarding productivity and pest control. For this model, 3 scenarios were chosen for pest control – no control, partial control and full control. “No control” indicates a situation in which the forest does not apply additional control measures and maintains “status quo.” Partial control represents a situation, in which the forest applies prevention techniques according to the U.S. implementation of ISPM-15 by Haack et. al (2014). Full control represents a situation in which the hypothetical invasive pest is fully controlled, and thus the pine is not affected.

Productivity is defined as the production of pulpwood, which although can be influenced by climate change itself, can also be affected by planting strategies. For purposes of this model, the effects on productivity from climate change were not included as there is still debate as to whether climate change will increase or decrease forest productivity (Susaeta, 2014). For the development of scenarios five productivity levels were used: 0.8, 0.9, 1.0, 1.1, and 1.2. A productivity level below 1 indicates decreased productivity, whereas a level above 1 indicates increased productivity. A productivity level of 1 indicates status quo productivity levels.

**Figure 9. Analytical Diagram Used For Calculating Timber Revenue**

In addition to level of pest control and productivity, four other variables were used in the development of this model – $g$, $\lambda$, LEV, and NPV. The descriptions and units for all 6 of these variables are summarized in Table 2.
To develop this analytical model, g, λ, and P were used to create a linear model for LEV. The purpose of developing a different model for LEV than the one suggested by Susaeta et. al (2014) was so that there were similar scales across the components in the diagram. Furthermore, Susaeta et. al utilized the rotation age of the trees in his model. Since we did not have this piece of data for Duke Forest, it served as another reason to adapt the model for LEV. Figure 10 shows regression plots that were developed using “R.” From these regression plots, average values, standard errors, and standard deviations were calculated for the coefficients of g, λ, and P in the linear fit to LEV. These coefficients were then used to calculate an intercept of the LEV model. Table 3 shows the final calculations with errors and p-values included for each of the coefficients. The linear model for LEV produced had a final R-squared value of 0.9974, indicating a strong correlation and linear fit. In terms of g, P and λ the equation for LEV was found to be:

\[ LEV = 649.2g + 2761.5p - 67898\lambda - 1700.08 \]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Units</th>
<th>Description</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>λ</td>
<td>events/year</td>
<td>Probability of arrival of a disturbance event in any given year</td>
<td>(Suseata et al., 2014)</td>
</tr>
<tr>
<td>g</td>
<td>proportion</td>
<td>Proportion of the stand that is salvaged after a disturbance event at time X</td>
<td>(Suseata et al., 2014)</td>
</tr>
<tr>
<td>P</td>
<td>proportion</td>
<td>Productivity Level</td>
<td>(Suseata et al., 2014)</td>
</tr>
<tr>
<td>LEV</td>
<td>$/ha</td>
<td>Land Expectation Value</td>
<td></td>
</tr>
<tr>
<td>Level of Pest Control</td>
<td></td>
<td>Decision between no control, partial control and full control</td>
<td>(Suseata et al., 2016)</td>
</tr>
<tr>
<td>NPV</td>
<td>$/ha</td>
<td>Net Present Value</td>
<td>(Suseata et al., 2016)</td>
</tr>
</tbody>
</table>
Figure 10. Plots of Data Used for Expressing LEV as a Function of Variables: $g$, $p$, and lambda.
Table 3. Coefficients for Resulting Linear Fits for Expressing LEV as a Function of Variables: lambda, p and g; R-squared value of 0.9974.

| Estimate  | Standard Error | t-value | Pr(>|t|) |
|-----------|----------------|---------|----------|
| Intercept | -1700.1         | 68.4    | -24.9    | <2e-16   |
| lambda    | -67898.0        | 538.0   | -125.0   | <2e-16   |
| p         | 2761.5          | 53.9    | 51.2     | 1e-04    |
| g         | 649.2           | 152.4   | 4.3      | 1e-04    |

As described previously, there were three levels of pest control. In order to account for the impacts of both climate change and pest control, an equivalent scale was necessary. Therefore, the percent reduction due to the control decision was modeled, assuming that the proportional change in NPV – the output for the pest scenario cases – would have an equivalent scaling to that of the proportional change in LEV. To calculate the percent reduction due to the control decision, values from Table 1 in Susaeta et al. (2016) were utilized. For both no control and partial control, the resulting NPV per each harvest age was found. This NPV was then divided by the NPV from full control, subtracting 1 to produce a percent reduction in NPV. For no control and partial control, the average values and standard deviations for this percent reduction were calculated across harvest ages. Overall, this produced values of -0.2468 for average reduction in NPV with a standard deviation of 0.0070 for a partial control scenario. For a no control scenario, this value was -0.3431 average reduction with a standard deviation of 0.0045. Furthermore, for a full control scenario, the percent reduction was 0 as the pest invasion would not affect the pine.

As the scenarios for pest control are now converted to proportional changes, they can be applied directly to the impacts from climate change. This combination of scales is conducted in the “Pest Invasion and Climate Change,” node. To do this, a final LEV is calculated after pest invasion and impacts from climate change for each scenario. It is modeled by the equation:

\[
\text{LEV}_{\text{climate change and pest invasion}} = \text{LEV} \times (1 + \text{level\_of\_control})
\]

Overall, this equation finds a final LEV by accounting for a reduction depending on the level of control due to a pest invasion and the LEV produced from the climate change calculations.

Next, to adapt this model so that it can be used to make predictions for the Duke Forest, the scale needed be combined again. This is conducted in the “Proportional Change” component. For this, 4 scenarios based on g = 0.3, 0.7 and \(\lambda\)=0.01, 0.05 were chosen. A table was produced for each scenario to model the overall proportional change in LEV.

In order to do this, the resulting values for LEV from the “Pest Invasion and Climate Change” node were used. These LEVs were then divided by the ‘ideal situation.’ The ideal situation was defined as one in which the P=1, the pest control is fully controlled, lambda = 0, and g=1. The ideal situation was based on practicality and one that most aligns with the Duke Forest’s current situation in a perfect year. In this case, the ideal situation was found to be $1711/hectare. Thus, proportional change was modeled by the following equation:

\[
\text{Proportional Change} = (\text{LEV} - 1711) / 1711
\]
**Table 4. Proportional Changes for $g=0.3$ and $\lambda=0.01$**

<table>
<thead>
<tr>
<th>Pest Control</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.8</td>
</tr>
<tr>
<td>No Control</td>
<td>-0.99</td>
</tr>
<tr>
<td>Partial Control</td>
<td>-0.99</td>
</tr>
<tr>
<td>Full Control</td>
<td>-0.99</td>
</tr>
</tbody>
</table>

**Table 5. Proportional Changes for $g=0.3$ and $\lambda=0.05$**

<table>
<thead>
<tr>
<th>Pest Control</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.8</td>
</tr>
<tr>
<td>No Control</td>
<td>-3.11</td>
</tr>
<tr>
<td>Partial Control</td>
<td>-2.96</td>
</tr>
<tr>
<td>Full Control</td>
<td>-2.57</td>
</tr>
</tbody>
</table>

**Table 6. Proportional Changes for $g=0.7$ and $\lambda=0.01$**

<table>
<thead>
<tr>
<th>Pest Control</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.8</td>
</tr>
<tr>
<td>No Control</td>
<td>-0.89</td>
</tr>
<tr>
<td>Partial Control</td>
<td>-0.88</td>
</tr>
<tr>
<td>Full Control</td>
<td>-0.83</td>
</tr>
</tbody>
</table>
Table 7. Proportional Changes for $g=0.7$ and $\lambda=0.05$

<table>
<thead>
<tr>
<th>Pest Control</th>
<th>0.8</th>
<th>0.9</th>
<th>1.0</th>
<th>1.1</th>
<th>1.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Control</td>
<td>-2.91</td>
<td>-2.69</td>
<td>-2.48</td>
<td>-2.26</td>
<td>-2.04</td>
</tr>
<tr>
<td>Partial Control</td>
<td>-2.72</td>
<td>-2.57</td>
<td>-2.37</td>
<td>-2.17</td>
<td>-1.97</td>
</tr>
<tr>
<td>Full Control</td>
<td>-2.42</td>
<td>-2.26</td>
<td>-2.10</td>
<td>-1.95</td>
<td>-1.78</td>
</tr>
</tbody>
</table>

Tables 4-7 show the resulting proportional changes in total LEV as a function of productivity and pest control for each of the four scenarios. After the overall proportional changes were calculated for LEV, these were adapted to calculate the projected timber revenue from pine for the Duke Forest. Forest data from the past 10 years was used to calculate the revenue per acre. On average, this value was $6250$ per acre with a standard deviation of $2556$. In addition, the 10-year projection for the number of acres of pine that will be harvested was utilized in the 10-year acres harvested, which was given as 443 acres. Finally, to calculate the overall revenue after impacts from climate change and pest invasions, the following equation was used to calculate the expected 10-year revenue from harvesting pine:

$$\text{Total Revenue} = (\text{money\_per\_acre} \times \text{10\_year\_acres\_harvest}) \times (\text{percent\_change} + 1)$$

Table 8 provides a summary for each component of the model and the calculations utilized as discussed.
<table>
<thead>
<tr>
<th>Node</th>
<th>Description</th>
<th>Units</th>
<th>Definition</th>
</tr>
</thead>
</table>
| Pest Control         | Input choice of level of pest control                                        |             | • No Control  
|                      |                                                                              |             | • Partial Control  
|                      |                                                                              |             | • Full Control                                                    |
| Mean Reduction_Partial | Distribution that assumes some level of control; the mean and standard deviation are based on the average reduction of NPV | Proportion  | Normal( -0.25, 0.007 )                                                   |
| Mean Reduction_No Control | Distribution to describe status quo; the mean and standard deviation are based on the average reduction of NPV | Proportion  | Normal( -0.343, 0.004 )                                                  |
| Full Control         | Distribution to describe full control – no impacts from pests                | Proportion  | 0                                                                       |
| Level of Control     | If statement to assign a value to the decision node                          | Proportion  | if pest_control='no control' then mean_reduction_no else if pest_control='partial control' then mean_reduction_partial else full_control |
| mu_g                 | Distribution that represents the coefficient for g in the linear fit for LEV | $/ha        | Normal( 649.2, 152.4 )                                                  |
| mu_lambda            | Distribution that represents the coefficient for lambda in the linear fit for LEV | $/ha        | Normal( -67898, 528.95 )                                                |
| mu_prod              | Distribution that represents the coefficient for productivity in the linear fit for LEV | $/ha        | Normal( 2761.5, 53.90 )                                                 |
| Productivity         | Decision that chooses productivity levels                                   | Proportion  | • 0.8  
|                      |                                                                              |             | • 0.9  
|                      |                                                                              |             | • 1.0  
|                      |                                                                              |             | • 1.1  
<p>|                      |                                                                              |             | • 1.2  |</p>
<table>
<thead>
<tr>
<th><strong>Intercept</strong></th>
<th>Distribution that represents the relationship between LEV and the intercept value in the linear fit for LEV</th>
<th>$/ha</th>
<th>Normal( -1700.08, 68.39 )</th>
</tr>
</thead>
</table>
| **g**        | List for 2 chosen scenarios for g                                                              | Proportion | 0.3  
|              |                                                                                                                                                     |      | 0.7                  |
| **lambda**   | List for 2 chosen scenarios for lambda                                                          | Events/year | 0.01  
|              |                                                                                                                                                     |      | 0.05                 |
| **LEV**      | Expression to represent the linear fit for LEV                                                 | $/ha | Intercept + (mu_lambda*lambda) + (mu_g*g) + (mu_prod*productivity) |
| **Pest Invasion and Climate Change** | Expression to represent the impacts from LEV, which expresses the impacts from storm events, and the impacts from pest control | $/ha | (Abs(LEV)*level_of_control)+LEV |
| **Proportional Change** | Tables indexed by the chosen scenarios for g and lambda to represent the overall proportional change in comparison to LEV/NPV | Proportion | See Tables X-Y |
| **10-year acres harvested** | Constant value to represent the projected 10-year harvest of pine from Duke Forests          | Acres | 443 |
| **Money per Acre** | Constant value to represent the estimated dollar revenue per acre harvested                   | $/acre | 6250 |
| **Total Revenue** | Equation used to find the total revenue projected revenue, accounting for climate change and pest invasion | $ | (money_per_acre * 10_year_acres_harvest) * (percent_change) + (money_per_acre * 10_year_acres_harvest) |
4.4. Predictions for Scenarios

Figures 12 – 15 show the aggregate revenue in terms of a 10-year projection for the Duke Forest. This is done for four different scenarios: \( g=0.3 \) and \( \lambda=0.01 \), \( g=0.3 \) and \( \lambda=0.05 \), \( g=0.7 \) and \( \lambda=0.01 \), \( g=0.7 \) and \( \lambda=0.05 \). As depicted in Figures 13 and 15, the Duke Forest has risk of operating at a loss for cases of extreme storms, but also has potential to still maintain a positive timber revenue for cases of reduced impacts from climate change.

**Figure 12. Total Revenue for \( g=0.3 \) and \( \lambda=0.01 \)**

![Graph showing total revenue for different levels of pest control and productivity for \( g=0.3 \) and \( \lambda=0.01 \).](image1)

**Figure 13. Total Revenue for \( g=0.3 \) and \( \lambda=0.05 \)**

![Graph showing total revenue for different levels of pest control and productivity for \( g=0.3 \) and \( \lambda=0.05 \).](image2)
Figure 14. Total Revenue for $g=0.7$ and $\lambda=0.01$

Figure 15. Total revenue for $g=0.7$ and $\lambda=0.05$
5. Discussion & Conclusions

5.1 Implications

As shown by the preliminary model predictions, it is likely that pest invasions and climate change will impact the Duke Forest’s timber revenue. Figures 13 and 15 show that if the effects from climate change and pest invasions are strong, then the Duke Forest has potential to lose money over the course of the next 10 years. This is very possible as the Harvard forest, which is located north of the Duke Forest has already experienced this outcome. From expert elicitation, it was found that the Harvard forest has not had a significant timber sale since 2008, when they cut over 40ha of declining spruce and red pine plantations (J. Thompson, personal communication, February 20, 2019). In order to mitigate these impacts on timber revenue, Duke Forest can take measures in order to increase productivity and fully control pest invasions. Furthermore, the revenue predictions are highly dependent on salvageability and disturbance risk. Therefore, if Duke Forest tends to have a high salvageable rate and low disturbance risk, it will likely be able to overcome many of the impacts from storms. In addition, if pest invasions are controlled for and the effects from climate change are smaller, the Duke Forest can still make money from timber. For example, if g=0.7 and λ=0.01, the Duke Forest can make $2.25 million from pine harvesting over the next 10 years if the proper precautions related to productivity and pest invasion control are taken into account. However, as the ideal revenue is $2.76 million, it is still recommended that the Duke Forest apply further measures besides productivity and invasive species control to get closer to their goal timber revenue value.

As shown from the development of the analytical model, it is clear that there are many complexities involved when quantifying an influence diagram. Often times, factors that cannot be modeled such as “future change in length of growing season” for the maintaining timber revenue model, need to be accounted for in a creative way. In this case, the change in length of the growing season was accounted for by modeling the more direct impacts of climate change such as storm events and salvageability. Furthermore, having a combined scale adds another complexity to the analytical model. For the timber revenue, this complexity was addressed through the use of calculating for proportional changes.

Overall, the development of the influence diagram and analytical model for the “maintaining timber revenue” sub-objective shows that a quantifiable model can be developed in order to help Duke Forest assess its risks to forest health and optimize for its management practices. This method can be applied for the other sub-objectives, eventually creating larger models for the fundamental objectives as described in Figure 1. The reliability of these analytical models including the one created will be highly dependent on the quantity and quality of available data from the forest, outside resources such as from literature and experts, as well as the amount of chance nodes that contribute uncertainty.

5.2. Shortcomings

Since this model was adapted from two studies and Duke Forest data, there was additional uncertainty created as a result of combining three different scales. The standard deviations and errors were all low for mean reductions from invasive species and for the linear
model for LEV. However, the revenue per acre had a lot of uncertainty in that the standard deviation was $2,556. This high standard deviation is likely due to uncertainties and fluctuations in the market such as market demand and supply, as well as variations in planting strategies. In addition, a potential way to mitigate the uncertainty is to use a different scale as opposed to acres. For example, the revenue per board foot was approximately $0.22 with a standard deviation of $0.03. Compared to the relative proportion from acres, this is significantly less. Thus, in the future, one can calculate the predicted board feet that Duke Forest will need to harvest in order to maintain timber revenue and use the associated revenue per board foot. However, it is still important to account for acres in some way in the model since Susaeta et. al (2014) found that planting fewer pine trees per hectare reduced damages caused by increased wildfire events and generates higher land values.

The revenue predictions shown in Figures 12-15 also has a lot of variability depending on $\lambda$ and $g$. Thus, when applying this model for decision analysis, it will be important to account for uncertainty in $\lambda$ and $g$, as well as to potentially make a strong, educated prediction for these values.

Furthermore, it would be interesting to utilize a method to propagate all of the errors for all of the components in the model to find a final uncertainty in the expected timber revenue, so that the Duke Forest management team can make decisions accordingly. Although this uncertainty would likely be useful to the Duke Forest, it is also important to account for other factors that might drive revenue changes. For example, stumpage prices, costs and returns from alternative land uses may also change in response to climate change (Susaeta et. al, 2014). Although these external market factors are accounted for in the influence diagram, it would be interesting to account for these in the analytical model. If timber prices were to rise, for instance, the Duke Forest may be able to overcome the negative impacts from loss of supply due to climate change. Also, according to Susaeta et. al (2014), changing climatic conditions can increase demand for forest biomass for bioenergy. In addition, carbon markets and payment for carbon sequestration could be additional factors to be accounted for in both the influence diagram and the analytical model for timber revenue. For example, carbon credits may play a strong role and have increased value due to the growing trend of policies oriented to ameliorate emissions of carbon dioxide.

For the invasive pest control, management of tree planting density and biological control are additional factors that can be included in the model (Susaeta, 2016). It will also be important to take into account the costs of increased productivity and pest control as this will reduce the overall revenue for the Duke Forest. Furthermore, it is important to note that this model removed harvest age as a variable and created models to account for the other factors. This removal can have implications on the final predictions. It could be beneficial to add harvest age as a variable to reduce uncertainty if the resulting propagated error for timber revenue is too high.

In order to improve the model, some additional steps can be taken. For example, one can work more with the Duke Forest and directly survey the forest in order to attain measurements with less uncertainty. In addition, with more forest data, one can better adapt this analytical model to create more reliable predictions for the Duke Forest. In addition, in the future, it will be important to develop the other sub-objectives and fundamental objectives into analytical models.
To do this, there should be more sources utilized in order to confirm results and minimize uncertainty. For example, more expert elicitation and surveys can be conducted to check outputs and methods of the model as well as to gather data that can be utilized. Furthermore, it would be interesting to test this model with other systems and forests to better confirm its reliability.

5.3. Outlook

It is likely that maintaining timber revenue will be a challenge that the Duke Forest will face in the future. However, it will be important to continue to develop this model and the rest of the models from the objectives hierarchy in order to properly assess decisions. A multiscale economic analysis of all of the factors that contribute to revenue for the forest may show that some methods will be more effective than others. It is possible, for instance, that focusing on external funding may be more effective management technique as it can generate a more reliable revenue source as opposed to allocating more resources to maintain timber revenue, which has more uncertainty. Thus, fully developing the objectives hierarchy for all fundamental objectives can have strong benefits to the Duke Forest.

This model, in general, has potential to be applied to other forest management systems as it creates a method in which one can simply change the decisions and constant variables to accommodate different forest systems. To do this, it will be important for the model to be as reliable as possible with minimal uncertainty. Thus, expert elicitation, testing and iterations should be conducted in order to do so. Overall, this method for conducting a risk analysis on the Duke Forest can help the forest as well as other forest systems to evaluate decisions and to optimize for resource allocation, assisting them in overcoming future risks and achieving their larger management goals.

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References


Thompson, J. R. (2019, February 20). Help with Student Project [E-mail interview].