
Linking Science and Management in a Geospatial, Multi-Criteria Decision Support Tool

Jennifer Pontius and James Duncan

Additional information is available at the end of the chapter

<http://dx.doi.org/10.5772/intechopen.73083>

Abstract

Land managers are often faced with balancing management activities to accomplish a diversity of objectives in complex, dynamic ecosystems. In this chapter, we present a multi-criteria decision support tool (the Future Forests Geo-Visualization Decision Support (FForGeoVDS)) designed to inform management decisions by capturing information on how climate change may impact the structure and function of forested ecosystems and how that impact varies across the landscape. This interactive tool integrates spatial outputs from various empirical models in a structured decision framework that allows users to customize weights for multiple management objectives and visualize suitability outcomes across the landscape. As a proof of concept, we demonstrate customized objective weightings designed to: (1) identify key parcels for sugarbush (*Acer saccharum*) conservation, (2) target state lands that may serve as hemlock (*Tsuga canadensis*) refugia, and (3) examine how climate change may impact forests under current and future climate scenarios. These case studies exemplify the value of considering multiple objectives in a flexible structure to best match stakeholder needs and demonstrate an important step toward using science to inform management and policy decisions.

Keywords: spatial modeling, landscape modeling, integrated modeling, GIS, structured decision-making, forest ecology, forest health, climate change, multiple criteria decision support, geo-visualization, Future Forests Geo-Visualization and Decision Support tool

1. Introduction

Over the past several decades, climate patterns across the globe have been shifting, accompanied by a wide range of biological changes. In the Northeastern US, it is predicted that climate change will continue to restructure forests and alter the services they provide over the coming century. To refine our understanding of how climate may impact forested

ecosystems, and how this information can be used to inform decision-making, our research group developed a spatial, multi-criteria decision support tool (Future Forests Geo-Visualization Decision Support (**FForGeoVDS**)) that integrates empirical models of current and future forest structure and function in an interactive weighting algorithm. Combined with climate projections, the resulting decision support framework allows stakeholders to compare outcomes for a variety of management objectives under various climate conditions on a pixel-by-pixel basis, thus reflecting the complexity of the Northeast's heterogeneous landscape. This merging of scientific knowledge with management needs is an important step toward improving our understanding of the relationships between forests and climate, but more importantly affecting change on the ground by informing management and policy decisions.

What makes this **FForGeoVDS** tool unique is several-fold:

1. The integration of disparate empirical ecosystem models allows us to incorporate and aggregate information on a variety of forest structural characteristics, processes, and ecosystem services provided. This set of ecosystem model inputs will be modified and updated over time as new models are developed and vetted by the scientific community.
2. The incorporation of several climate projection scenarios allows users to examine potential changes in modeled forest structure and function under alternative climate conditions.
3. A dynamic structured decision framework allows users to interactively select and weigh multiple management objectives for an integrated assessment of their overall management goals.
4. The structured decision framework is applied independently to each 30 m pixel across the landscape, providing spatial detail not typically included in decision analyses. This allows land managers to visualize outcomes across the landscape and identify various locations ideally suited for specific outcomes or those best suited to accomplish multiple outcomes.
5. The ability to continually expand and update the tool via the integration of new ecosystem models as they become available.

The overall goal of this chapter is to provide a test case for how the **FForGeoVDS** tool can integrate disparate research products in a structured decision support tool to provide spatially detailed quantification of the relative likelihood of meeting multiple objectives under both current and future climate scenarios. Here we give an overview of the **FForGeoVDS** tool's spatial modeling framework and demonstrate the general structure based on the integration of five empirical models developed to quantify: sugar maple distribution and health, forest fragmentation risk and hemlock distribution, and vulnerability to hemlock woolly adelgid (HWA). Using the **FForGeoVDS** tool, we present three case studies to demonstrate how these models can be integrated to visualize and prioritize locations across the landscape that meet a variety of management objectives. These case studies correspond to three hypothetical users with a decision to make:

- A Land Trust Director who wants to identify private properties for possible acquisition to both conserve sugar maple habitat and minimize forest fragmentation on habitat corridors;
- A State Forest Planner who wants to identify a state forest for hemlock monitoring and possible stand improvement where hemlock is likely to tolerate hemlock woolly adelgid infestation in order to maintain important wildlife habitat; and
- A Climate Action Advocate who wants to demonstrate how our ability to maintain both sugar maple and hemlock across the state is likely to change with the twin pressures of forest conversion and projected climate change.

This demonstration exemplifies a structured algorithm for decision support and an optimized spatial output to visualize and assess relative objective success across the study area. However, it is important to note that this approach is not designed to serve as an optimization exercise that differentiates among management alternatives. Instead, it serves as a spatial assessment and visualization tool to allow users to identify where across the landscape priority management objectives are most likely to be successful under status quo management activities, and how this might change under climate change scenarios. It also does not permit assessment of management objectives or alternate scenarios that are not already captured in modeled inputs or spatial data layers. As such, it is limited by the ecological modeling products available. However, we anticipate that over time, additional ecological models can be incorporated into the decision tool based on feedback on stakeholder needs and continued progress in scientific modeling for the region.

This development of the **FForGeoVDS** tool has been aided by a broad audience of stakeholders who have been continually involved in the design process. The research team has held multiple participatory design sessions with professionals from multiple state and federal agencies, nonprofit land management organizations, and advocacy groups. These stakeholders have provided invaluable input into the necessary features and functionality of the decision support tool, as well as how this tool will be situated in the larger ecosystem of tools available to support decision-making about Vermont's forests. While many tools exist from many different agencies, there is a notable gap in the ability of managers to combine projections of climate change with forest management objectives in a flexible way pertinent to their scale and extent of interest. This puts the **FForGeoVDS** tool in a particularly good position for adoption and use, and these stakeholder engagement sessions have helped to shape both the research team's activities and the expectations of the eventual users of the tool.

2. Background on decision support for forest management

The use of decision support systems is gathering increased attention in natural resource management because of the demand for increasing transparency, potential for economic, legal, and political conflicts, the increasing volume of data available to help inform decisions, and

improved technologies to integrate, analyze, and summarize this information [1]. This is particularly true for forest ecosystem management, where growth and yield models can be used to directly predict forest response to management alternatives [2]. Such tools are also proving useful when applied to adaptive management decisions, particularly as it relates to the impacts of climate change [3, 4].

There are many methodological approaches to decision support, including artificial neural networks, knowledge-based systems, and multi-criteria decision models [2]. While the aggregation algorithms differ, decision support systems are built on a basic framework that includes structuring the decision problem, identifying various alternatives or scenarios to compare, determining the preferences of decision-makers, and evaluating and comparing the decision alternatives [5]. Choosing the appropriate decision support methodology is dependent upon the actors that are involved in the process, desired goals, and available information [6].

Here we developed an interactive, multiple criteria, structured decision framework to help land managers visualize how climate change may impact forest structure, conditions, and processes across the landscape. Multiple criteria decision systems (MCDSs [7, 8]) provide flexibility in the selection and weighting of management objectives using a structured framework for evaluating outcomes for multiple, potentially conflicting objectives in quantitative units or qualitative rankings. This framework involves three main concepts: value scaling (or standardization) of various objectives, criteria weighting by the user, and a combination (decision) rule to aggregate across criteria [9] to evaluate the relative value of each alternative scenario in achieving the desired weighted objectives [6]. A key component of this approach is allowing decision-makers to determine which objectives are of interest, and what relative weights each of those objectives should carry in the analysis.

This approach is becoming more common in natural resource management applications to evaluate and compare broad alternatives for specific parcels or management units. More recently, it has become common to integrate temporal and spatial results to produce spatial decision support systems by coupling with GIS tools [9, 10]. For example, the integrated grid based ecological and economic (INGRID) landscape model, was developed by [11] to support landscape management decisions. INGRID was designed to simulate the ecological effects of management alternatives and costs for dry grasslands using empirical models that predict the risk of plant and animal extinction under alternative conditions, management scenarios, and disturbance regimes. While input rasters were spatially explicit, the resulting decision assessment was based on overall proportion of cells with desired biodiversity outcomes, without examination of spatial patterns in those outcomes across the landscape.

However, this same approach could be applied in a geospatial model where each pixel across the landscape is processed through the structured decision framework and evaluated independently. The name "Geovisual Analytics for Spatial Decision Support" [12] suggested for this approach emphasizes the importance of interactive, visual interfaces, as an effective way to synthesize and quantify information to support problem-solving. This requires an approach that first articulates decision objectives, integrates information from a multitude of data, provides a flexible, interactive interface for customization, and then provides data analysis and visualization, across multiple scenarios in order to select the right course of action

and where across the landscape that can be achieved [12]. Because this approach is typically disseminated through online visualization tools, it has the potential to provide access to a wider audience of potential stakeholders, enabling many actors to work together and providing an interface adaptable to the needs of different actors [12].

This highlights one of the key components of what can be a generally “techno-centric” approach to decision support: stakeholder engagement. The human decision-makers are an integral component to decision-making, providing information that often dominates the process [13]. Solutions based on complex algorithms, frameworks, and models can be integrated with approaches, such as collaborative learning, expert models, and continuous stakeholder participation during development in order to design systems better able to cope with the complexities of managing ecosystems with the potential for many conflicting interests [14].

Looking ahead, the future of decision support systems for forest management will likely move toward more comprehensive forest models and the need to consider climate change as a major driver [15]. This will require careful parameterization and empirical validation before implementation in decision support tools and at the same time will increase the required expertise to actually run the models and analyze the resulting output [16]. The Future Forests Geo-Visualization Decision Support (**FForGeoVDS**) tool presented here exemplifies this move toward more comprehensive, integrated forest models with parameterization for various climate-change scenarios. Other promising developments include the use of the Internet to enable easy access to data and public engagement with these tools and the resulting outputs. This presents an opportunity for new decision support applications, such as the one presented here, to bring decision support to a broader audience of public, commercial, nonprofit, and private stakeholder groups.

3. Approach

Here we demonstrate the structure and utility of the new multi-criteria Future Forests Geo-Visualization and Decision Support (**FForGeoVDS**) tool, designed to integrate empirical models of forest structure and function under various climate conditions. This pilot is based on several current empirical models (forest fragmentation risk, sugar maple abundance, sugar maple canopy condition, eastern hemlock abundance, eastern hemlock HWA risk), integrated in three user case studies. Here we walk through various components of the **FForGeoVDS** approach, including a summary of the empirical models that provide the foundation for the decision support tool (Section 3.1), the geospatial interface used to integrate across models (Section 3.2), customized weighting scenarios (Section 3.3), and the structured decision calculations (Section 3.4) used to aggregate decision outcomes. The final outputs include maps that quantify the weighted suitability (Section 3.5) on a pixel-by-pixel basis, highlighting where management objectives are most likely to be met and providing a quantitative basis for parcel comparison.

Because of the flexible design of the **FForGeoVDS** tool, we are able to demonstrate how the mean “weighted suitability” decision outcome can be captured across the landscape and compared across towns, parcels, and climate scenarios to inform three different customized management objectives (Section 4).

3.1. Input empirical models

The **FForGeoVDS** tool relies on empirical models designed to capture specific ecosystem structure and function that can be used as a proxy for management outcomes. Here we incorporate five disparate models: tree species distribution (sugar maple and hemlock percent basal area maps [17]), forest fragmentation risk [18], sugar maple canopy condition [19], and eastern hemlock susceptibility to hemlock wooly adelgid [20]. For all input models included in any decision support tool, it is critical to provide easily accessible information about model development and validation to add credibility to the tool and allow stakeholders to assess the reliability of the resulting products. Here we present a brief summary of each model included in this pilot, including links to publications for additional information.

3.1.1. Tree species distribution model

Traditional forest classifications are often limited to coarse forest type classes, but advancements in remote techniques allow for more detailed mapping of species abundance and composition. This is particularly useful in the Northeast where species composition is often mixed and information beyond “dominant species” is required.

For the models included here, [17] employed a spectral unmixing technique based on multi-temporal Landsat imagery to capture the proportion of each species present in each pixel. Algorithms based on US Forest Service Forest Inventory and Analysis plots were used to convert spectral unmixing scores to basal area composition. Combining basal area maps for all key species, fractional basal area was calculated to quantify relative abundance of each species and to develop a thematic species map for comparison to more traditional species mapping products (**Figure 1**). Validation with 50 field inventory plots showed the resulting thematic forest classification mapped 15 forest classes with overall accuracy = 42%, KHAT = 33%, fuzzy accuracy = 86% at the pixel level, providing more detail and higher accuracy than existing forest-type mapping efforts.

Model description [17]:

Units: Percent basal area (0–1).

Spatial extent: Northern New York, Vermont, and New Hampshire; Western Maine.

Resolution: 30 m.

Time interval: Historic and current.

Climate: No significant climate influence.

3.1.2. Forest conversion model

To assess potential future changes in forest cover, [18] measured historical changes in forest cover in the northern forest region and used correlations between these historical changes and

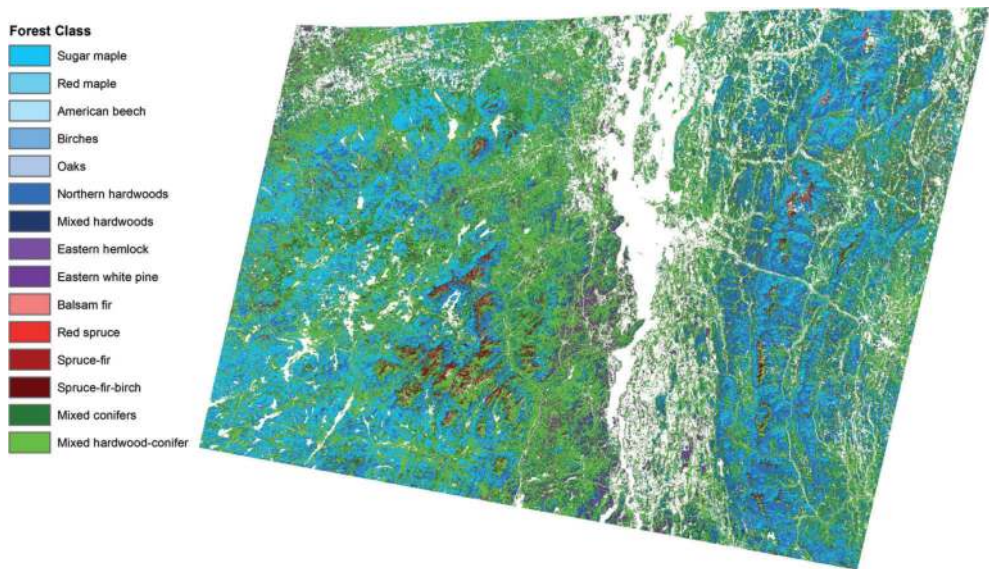


Figure 1. Forest cover map spanning northern New York and Vermont produced by integrating spectral unmixing of multi-temporal Landsat imagery and a rule-based, OBIA classification scheme.

other spatial variables to estimate future transitions into and out of forest at three time steps across the landscape.

This forest conversion model can be used to prioritize conservation in critical areas where deforestation is likely, or where projected deforestation will cause significant fragmentation of the landscape. It can also be used to avoid areas with high fragmentation risk if the management activity will not be able to control that process.

Resulting forest conversion probability maps (**Figure 2**) provide projections of places likely to experience deforestation or forest regrowth, but only insofar as historical drivers remain constant; this assumption may be weaker for later time frames.

Model description [18]:

Units: Probability of change (0–1).

Spatial extent: Northern New York, Vermont, and New Hampshire; Western Maine.

Resolution: 30 m.

Time interval: Historical, current and probability of transition maps available for 2030, 2060, and 2075.

Climate: No significant climate influence.

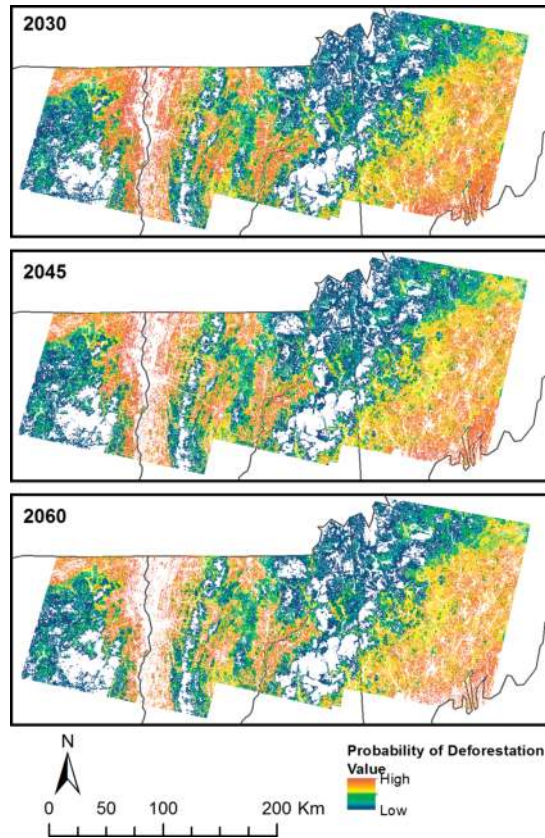


Figure 2. Probability maps show the likelihood of transition from forest to nonforest for each of three time steps. Higher values represent a higher probability (0–1 scale) of deforestation. Lower values indicate locations where deforestation is unlikely.

3.1.3. Sugar maple stress index model

This study compared a suite of climate metrics to field assessments of sugar maple canopy condition across Vermont [19]. Five climate metrics were significantly related to sugar maple decline. The influence of climate is comparable to that of insect outbreaks and other disturbance events, indicating that in Vermont, sugar maple is a climate-sensitive species.

The model identified areas across the state where climate has historically been better or worse for sugar maple (**Figure 3**). Substituting climate projections in the model indicates that climatic conditions are likely to become less favorable for sugar maple over time, with up to 84% of current sugar maple stands negatively impacted by climate change. However, locations of “climate refugia” should also be available to maintain sugar maple in spite of changing climatic conditions. Considering the role of sugar maple in Vermont’s economy and culture, managing this resource into the future as climate changes is of great concern and could pose a considerable challenge.

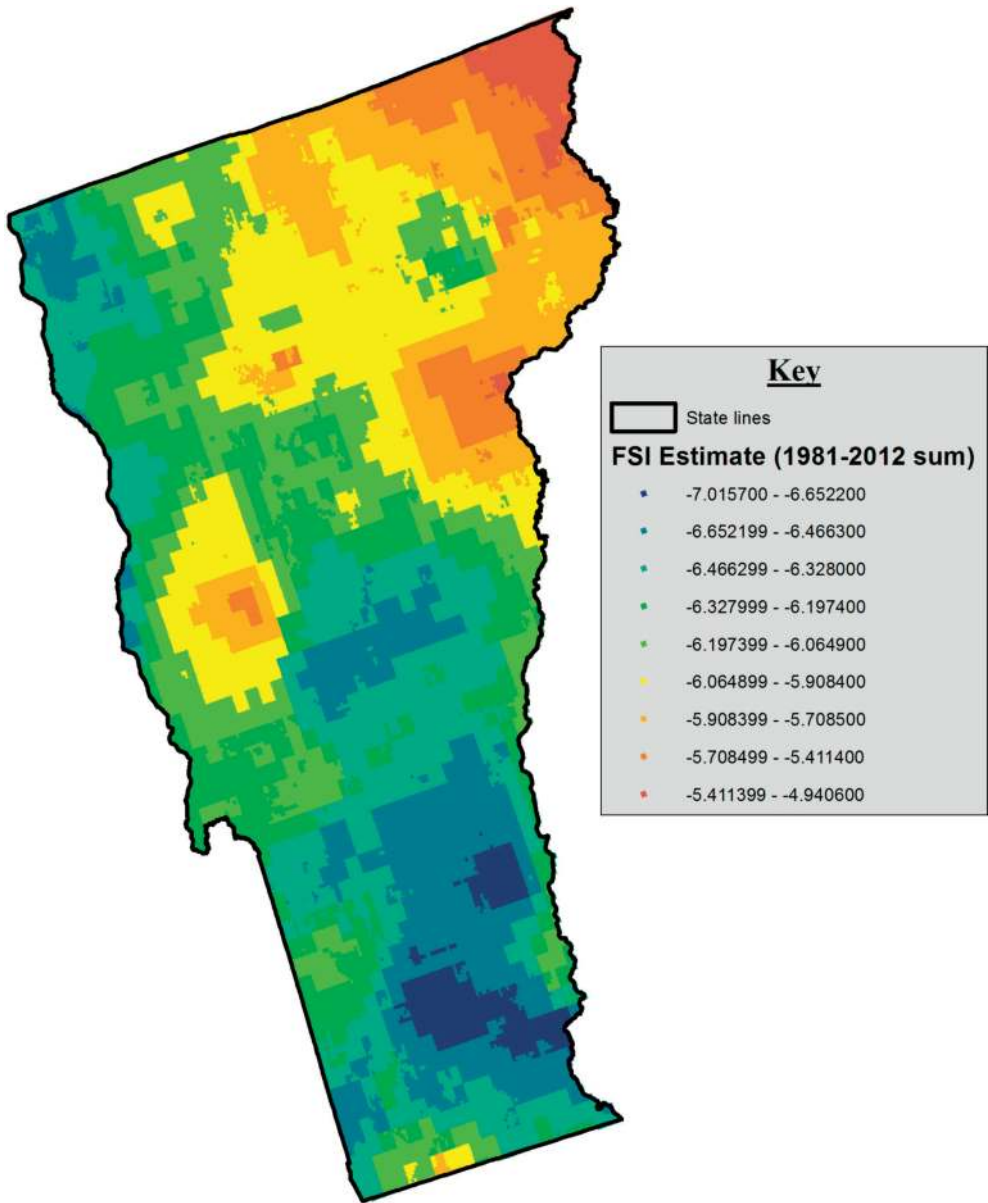


Figure 3. Climate impacts on sugar maple health from 1981 to 2012. Higher forest stress index (FSI) values (warmer colors) represent locations with more severe climate induced sugar maple decline over the historical record. Lower FSI values indicate locations with minimal climate induced sugar maple decline.

This study was designed to isolate the impacts of climate on sugar maple condition and does not capture additional stressors that may result from other biotic or abiotic agents. As such, it should be used only to differentiate relative regions of climate favorability for sugar maple.

Model description [19]:

Units: Forest Stress Index (FSI) near 0 represents average canopy condition, Lower values = healthier than normal, Higher values = higher decline than normal.

Spatial extent: Vermont.

Resolution: 800 m.

Time interval: Historic (1971–2000 norms), current (1981–2010 norms), and projected (2050 and 2100 under two climate scenarios).

Climate: Significant climate influence captured for A2 (high) and B1 (low) emission scenarios.

3.1.4. Hemlock woolly adelgid susceptibility model

To measure the relative risk of hemlock woolly adelgid (HWA)-induced decline in eastern hemlock stands, [20] quantified changes in hemlock basal area increment (BAI) to quantify decline on 41 hemlock stands across New England. They determined that slope, GIS calculated Hillshade (capturing heat load), and January minimum temperatures were significant predictors of hemlock decline rates following infestation. The authors built a model to differentiate stands likely to decline rapidly (susceptible) from those likely to decline over longer time periods (tolerant) (**Figure 4**). The model correctly classified 80% of the 41 original sites with 73% accuracy on 15 independent validation sites.

To apply this model across the study region, GIS data layers for key input variables were used to produce a spatially explicit model that predicts the likelihood of hemlock growth declines following HWA infestation. This was applied using both historical temperature norms and a projected 2°C increase in minimum January temperatures.

Model description [20]:

Units: Probability of rapid HWA-induced growth decline (0–1 scale).

Spatial extent: New England.

Resolution: 30 m.

Time interval: Historic (1971–2000 norms), current (1981–2010 norms), and projected (2050 and 2100 under two climate scenarios).

Climate: Significant climate influence captured for A2 (high) and B1 (low) emission scenarios.

3.2. Geospatial integration

Integration of many spatial data layers requires careful preprocessing. These inputs include empirical model inputs (raster layers) as well as other ancillary data necessary in

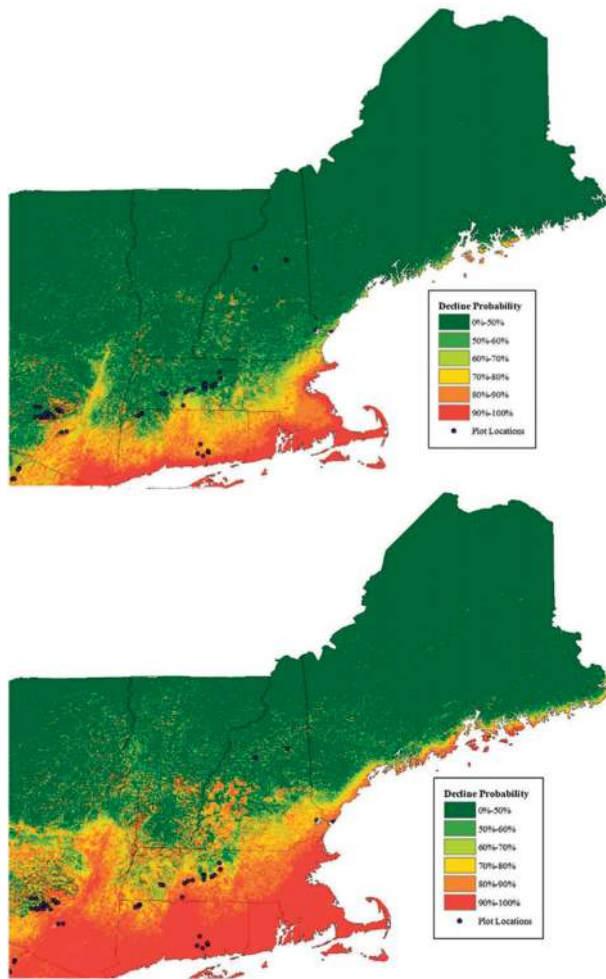


Figure 4. Hemlock risk map shows probable locations of declining sites for current (top) climate and projected (bottom) climate conditions. Map units capture the probability quartile (0–50, 50–60, 60–70, 70–80, 80–90, 90–100%) that a given location has site conditions favoring rapid hemlock decline. High values indicate locations where mortality will occur quickly following HWA infestation. Low values indicate locations where hemlock is likely to tolerate HWA infestation.

customizing the decision framework (e.g. land ownership class, political boundaries, etc). The first step was to develop a common raster grid framework to which all data were transformed. The 30-m USGS DEM for Vermont was used as the base frame for standardizing the various input data, providing the common projection (USA Contiguous Albers Equal Area Conic USGS), cell size (30 m), extent and snap raster for aligning all inputs to a common grid. Each input raster was projected, clipped to the extent of the Vermont study area, and then resampled to the common grid cell size and alignment. Continuous variables

were interpolated using bilinear resampling, while categorical variables were interpolated using the nearest neighbor resampling.

In order to integrate these outputs, each was first normalized to the same relative zero to one scale. When necessary, a percentile-based linear transformation was used to convert values for each pixel to a scale where 0 represents the lowest values for that metric and 1 represents the highest value for that metric. Units indicate the percentile value for a given value within the larger population of values contained in the input raster for the full study area raster. Species percent basal area for hemlock and sugar maple as well as the hemlock woolly adelgid probability risk model did not require any transformation as they generate data on a zero to one scale. The Forest Stress Index data ranged from -0.176002 (historical norms) to 2.166101 (A2 scenario). The probability of forest conversion was available for three time steps (2030, 2060 and 2075); to flatten these into a single raster, the maximum probability of conversion was calculated for each cell and used as the final input to the decision support tool. This processing was accomplished with a combination of Python scripts and ArcGIS models and run in the ArcGIS 10.4 software package.

3.3. User customization

The **FForGeoVDS** online tool requires that users first select their desired management objectives from the list of empirical models available. Here we include empirical models designed to capture forest structure or condition attributes described above (Section 3.1). Users select their desired management objectives, define an area of interest, weight each objective based on their overall management priorities, and define the directionality for each objective. The area of interest is used to calculate summary statistics and generate final maps. The weightings of each objective must sum to 100. The directionality of each objective determines whether higher values from the empirical model correspond to higher desirability for the user. As an example, higher probability of conversion may be desirable from someone looking for areas to purchase development rights, while lower probabilities of conversion may be desirable for someone looking to establish long-term monitoring plots. Once these customizations are set, the user can generate suitability maps of their chosen landscape.

3.4. Suitability calculations

FForGeoVDS calculates a suitability score for each pixel in the defined area of interest from the user-defined weights and directionality for each objective (**Figure 5**). Using the normalized input rasters, it is relatively easy to apply user-defined weights to calculate an overall “weighted mean suitability” score. Normalized values for each pixel are used as inputs to a weighted mean calculation based on user-defined weights. The desirability settings are incorporated by inverting the zero-to-one scores as needed such that positive values capture desirable outcomes and negative values capture undesirable values. The result is an integrated, weighted mean where higher value pixels identify where across the landscape the stated combination of management objectives is most likely to be met (**Figure 5**).

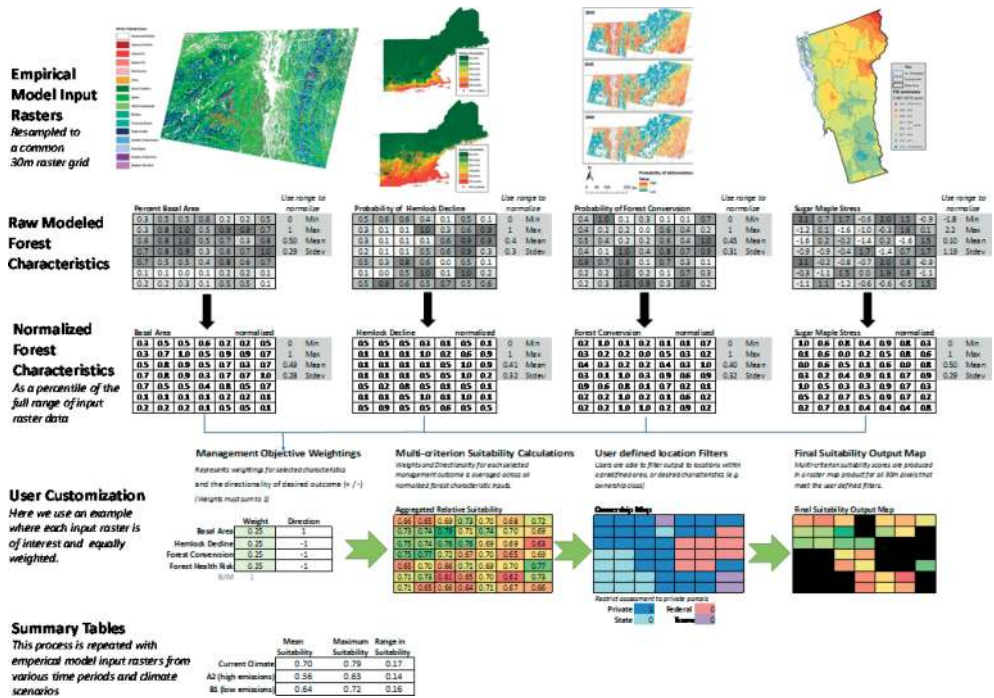


Figure 5. The GIS model used to calculate final suitability scores includes processes to normalize each selected input raster, rescale to match desired outcomes, weighted based on user customization and averaging for each pixel across the input study area. The resulting output suitability rasters are then summarized for the user-defined area of interest.

3.5. Suitability outputs

Outputs from the customization **FForGeoVDS** tool include maps of **weighted average suitability** outcomes where 0 represents the least suitable locations and 1 represents the most suitable locations for the specified combination of management outcomes. Users can manipulate a threshold to filter out pixels that do not meet a desired level of suitability. In addition, weighted average suitability data are summarized for user-defined areas of interest, including mean-weighted average suitability and the proportion of pixels above any user-defined thresholds of suitability. In this way, users can quantitatively compare both the extent and magnitude of suitability in addition to visualizing patterns across the landscape. With the addition of ancillary data layers as filters or for zonal statistics, users can use suitability values to compare properties for targeted efforts, relative success of various management objectives for a given property or the potential changes in suitability under various climate change scenarios. With this summary statistical information, users have critical information on which to base decisions and to more effectively communicate how management success is likely to change under various scenarios.

It is important to point out that the suitability score produced using the **FForGeoVDS** tool provides a 0–1 suitability scale based on the *full population* of conditions captured in the database across the full study area. Thus, if the user selects only their parcel for analysis, the scores

that are returned do not represent the best and worst locations for that specific parcel only, but instead returns scores that are relative to the best and worst locations for the entire area captured in the database (in this example, across the state of Vermont). As such, it is possible that a given property may contain no highly suitable locations relative to what is available across the state. If at the end of this analysis no “best” location to achieve management goals has been identified, this does not mean that the analysis was worthless. Often the insights gained may suggest other management options, rather than seeking outcomes that may not be likely given the conditions within a selected area. Because this analysis is flexible, the decision-maker is always free to explore other management objectives available in the tool to identify what that given parcel may be best suited for.

Another approach to decision support for clearly defined locations involves limiting normalization and subsequent suitability calculations to the range of values contained within the user-defined area rather than the full population of values across input rasters. One widely adopted approach to this location-specific analysis is the Simple Multi-attribute Rating Technique (SMART [21]). SMART analyses create an interval scale for each metric, and then base aggregation algorithms on the range of those scores within the specific decision problem area [22], not the range of all scores across the broader landscape. This is particularly useful when the range of possible scores is limited within a specific problem, which can limit the influence for that particular objective relative to other objectives in the multi-criteria problem. SMART weighted aggregation methods then allow the user to obtain a measure of the overall benefits of various locations relative to other locations only within the decision problem area. However, this approach is not suitable for all circumstances, for example when scores relative to other locations outside of the specified area are also of interest, or when there is a possible interaction between the some of the criteria [22].

While this tool has been purposefully designed to examine relative suitability across the entire study area, and considering the full range of information available within our input models, it can easily be modified to use the SMART approach described above. Future iterations of the **FForGeoVDS** tool will include user preference options to base normalization on the full range of population values (*population*) or to limit normalization to the range found only within the user-defined area (*SMART*). We also anticipate creating an option for users to aggregate using the *weighted average* or *additive weights* option. This further flexibility will allow for users to customize the type of information that output maps and tables are able to provide.

4. Use case studies

Here we present three hypothetical case studies to demonstrate different ways that the tool can be used to inform management. This includes customized objective selection and weights defining the relative importance of each objective, as well as a directionality statement defining whether high or low values are desired as ideal outcomes for each management objective.

These customized settings were then linked to our input empirical models to examine how suitability varies across the landscape, identify target management locations, and, where

Land Trust Director (Sugar Maple Focus)		
Objectives	Weight	Desirability setting
Sugar maple basal area	40	High desirable (1)
Hemlock basal area	0	
Sugar maple stress	40	Low desirable (-1)
Hemlock susceptibility	0	
Forest conversion risk	20	High desirable (1)
<i>Sum</i>	<i>100</i>	

Table 1. Customized objective weights and desirability settings to identify high sugar maple abundance, high conversion risk, and low climate-induced stress for sugar maple across the area of interest.

climate was identified as a potential driver, compare how suitability outcomes may change under different climate conditions. Note that not all management objectives will have climate scenario products. Some of the empirical models included here have found significant climate effects, resulting in products for multiple climate scenarios (e.g., sugar maple condition and hemlock risk). Other empirical models (e.g., fragmentation, species distributions) found no relationship between climate variables and thus do not include different climate scenarios for comparison in the **FForGeoVDS** tool.

4.1. Case study 1: land trust director

Context: A hypothetical land trust organization can secure funds to acquire new properties for conservation. The land trust has a focus on promoting habitat connectivity, and the donor is interested in the iconic sugar maple. Combining these, the land trust’s goal is to identify private properties that are (1) dominated by sugar maple, (2) at higher risk of development, and (3) at a lower risk of climate change-induced maple decline, weighted as described in **Table 1**. They will use output information to identify parcels best able to provide sugar maple refugia under climate change, while also maintaining forest connectivity.

Area of interest: Private, nonconserved lands in Vermont.

Input empirical models: Sugar Maple Stress Index Model, Percent Sugar Maple Basal Area, Forest Conversion Model.

Ancillary data layers:

Town boundaries and parcel boundaries – Vermont Centre for Geographic Information.

Habitat connectivity: Vermont Habitat Blocks and Wildlife Corridors: An analysis using Geographic Information Systems, Vermont Fish & Wildlife Department, 2011, by Eric Sorenson - Vermont Fish & Wildlife Department and Jon Osborne - Vermont Land Trust.

Conserved Lands, Vermont Protected Lands Database, Vermont Centre for Geographic Information. Last updated 2016.

Summarize by: Town and parcel.

Climate scenarios: Sugar Maple Stress Index Model with inputs for Historic norms, A2 (High emissions) and B1 (low emissions) scenarios.

Output maps (**Figure 6**) of this weighted prioritization of high sugar maple abundance and low sugar maple climate induced stress, with high risk of conversion, show that management suitability on private lands across the study area varies geographically, with ideal conditions concentrated in northern and central Vermont. It is also clear that climate change has the potential to decrease suitability considerably across the landscape, although with effects that differ geographically.

The user has defined the area of interest as private lands overlapping habitat with high connectivity value and set a suitability threshold of 60 to summarize output data. Within this area of interest, summary statistics were generated for each town (**Table 2**), allowing the hypothetical user to identify potential regions to target for land acquisition. These summary statistics identify several towns where the prioritized management objectives are likely to be met (highest mean suitability values for pixels above the 60 threshold). Zonal statistics, output in table format, summarize the mean suitability score above the threshold, area of the town above a threshold, and the percent of the total town area that meets the suitability threshold. This allows of hypothetical land trust to prioritize locations to search for potential conservation properties. Under historical norm climate conditions, St. Albans Town comes out as a top location, with the highest mean suitability score and over 1.2 million hectares that meet at least a 60th percentile for suitability.

However, considering future climate conditions, a new ranking emerges due to differential projections of climate change across the study area (**Table 3**). Under the low and high

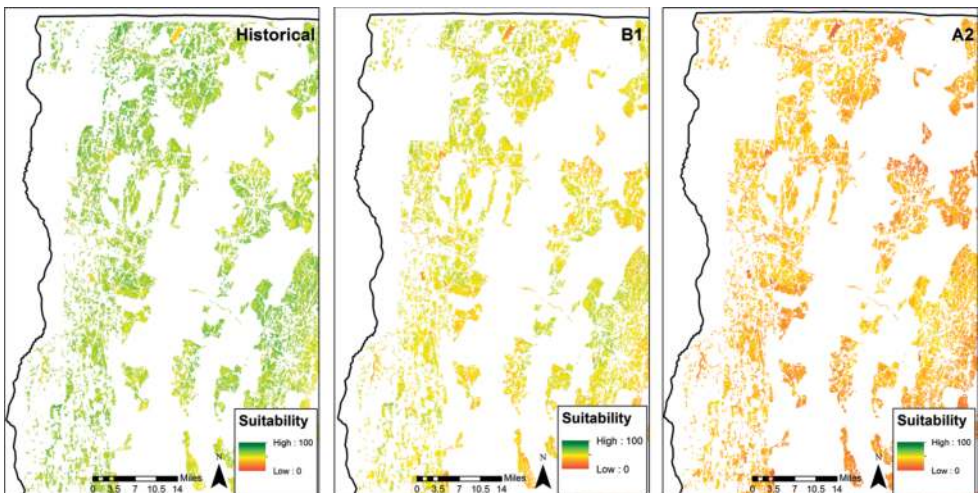


Figure 6. Output maps of weighted suitability for every 30 m pixel where sugar maple is present on privately owned parcels across the selected study area demonstrate how relative suitability differs geographically and under various climate change scenarios.

Summary Statistics by Town—Current Climate			
Town	Mean suitability above threshold	Area above threshold (ha)	% Town area
St. Albans	70.1	1,215,486	9
Montpelier	69.9	729,567	31
Highgate	69.6	2,532,465	18
Swanton	69.4	1,430,865	10
Berlin	69.3	1,458,972	17
Franklin	68.7	2,008,881	21
Waterbury	68.5	807,084	7
Mooretown	68.5	820,449	9
Fairfield	68.4	3,899,907	24
Georgia	68.2	2,588,922	25

Table 2. Summary statistics on suitability outcomes under current climate conditions are summarized by the towns and sorted by mean suitability above a 60 suitability threshold.

Town	Mean suitability above threshold	Area above threshold (ha)	% Town area
Summary Statistics by Town—B1 Low Emissions Scenario			
Orange	63.6	2,106	0
Addison	63.5	120,528	1
Troy	63.2	209,223	2
Highgate	63.1	628,641	4
Newport	63.1	127,494	1
Irasberg	63.0	216,594	2
Barton	62.9	70,551	1
Montpelier	62.8	228,420	10
Johnson	62.7	57,834	1
Weybridge	62.7	95,013	2
Milton	62.7	476,928	3
Summary Statistics by Town—A2 High Emissions Scenario			
Troy	60.6	648	0
Franklin	60.3	81	0
Highgate	60.0	81	0

Note, only those towns with area above the 60 suitability threshold are included.

Table 3. Summary statistics on suitability outcomes under the B1 (low emissions, upper) and A2 (high emissions, lower table) climate scenarios are summarized by town and sorted by mean suitability above a 60 suitability threshold.

emission scenarios, mean suitability and area above the 60th percentile threshold drop for all towns. But this drop is more significant for some, with St. Albans Town dropping off of the top 10 list for both low and high emission scenarios entirely. This indicates that if the Land Trust wants to consider sugar maple resilience under future climate conditions, the town of Orange (low emission) or Troy (low and high emissions) is likely to have more suitable locations. However, the area above the 60th percentile threshold is low for both towns, indicating that it may be difficult to find available properties for conservation efforts. If the small proportion of parcels that are most suitable for purchase are not for sale, the Land Trust could target a town such as Troy, VT that has a similar mean suitability but over a much larger area.

Parcel maps can then be used to identify key properties to target within the town of Troy for conservation purchase. The suitability output maps (**Figure 7**) show us that there are several properties with a high suitability score for potential conservation efforts.

This exercise allows the Land Trust to identify and compare potential properties for sugar maple conservation in locations where forest conversion risk is relatively high, but sugar maple abundance and resilience in the face of climate change are also high. This represents a tangible, decision product that can be used to guide and justify actions taken by the Land Trust to preserve potential sugar maple refugia and attract potential funding.

4.2. Case study 2: state forest planner

Current models suggest that hemlock woolly adelgid will disperse through the majority of eastern hemlock's native range, but with impacts that vary widely depending on site conditions. This hypothetical state forest planner wants to identify hemlock stands within state forests that contain high-density eastern hemlock stands that are most likely to tolerate HWA infestation, weighted as described in **Table 4**. The goal is to manage for hemlock in areas that are likely to serve as long-term seed source for this species.

Area of interest: Vermont State Forests.

Input empirical models: Percent Hemlock Basal Area, Forest Conversion Model, Hemlock Risk Model.

Ancillary data layers: Conserved lands, Vermont Protected Lands Database, Vermont Centre for Geographic Information. Last updated 2016.

Summarize by: Forest management unit.

Climate scenarios: Hemlock Risk Model with inputs for Historic norms, A2 (high emissions), and B1 (low emissions) scenarios.

Output maps of this weighted prioritization of high hemlock abundance and low hemlock risk on state lands indicate that much of the state's forest land is suitable for hemlock management under current climate conditions (**Figure 8**). However, some state forests, particularly those in central and eastern VT, are particularly at risk from the invasive HWA under future climate scenarios. In particular, we begin to see the impact of heat and water stress on the relatively drought intolerant hemlock manifest in lower suitability scores on southern facing slopes.

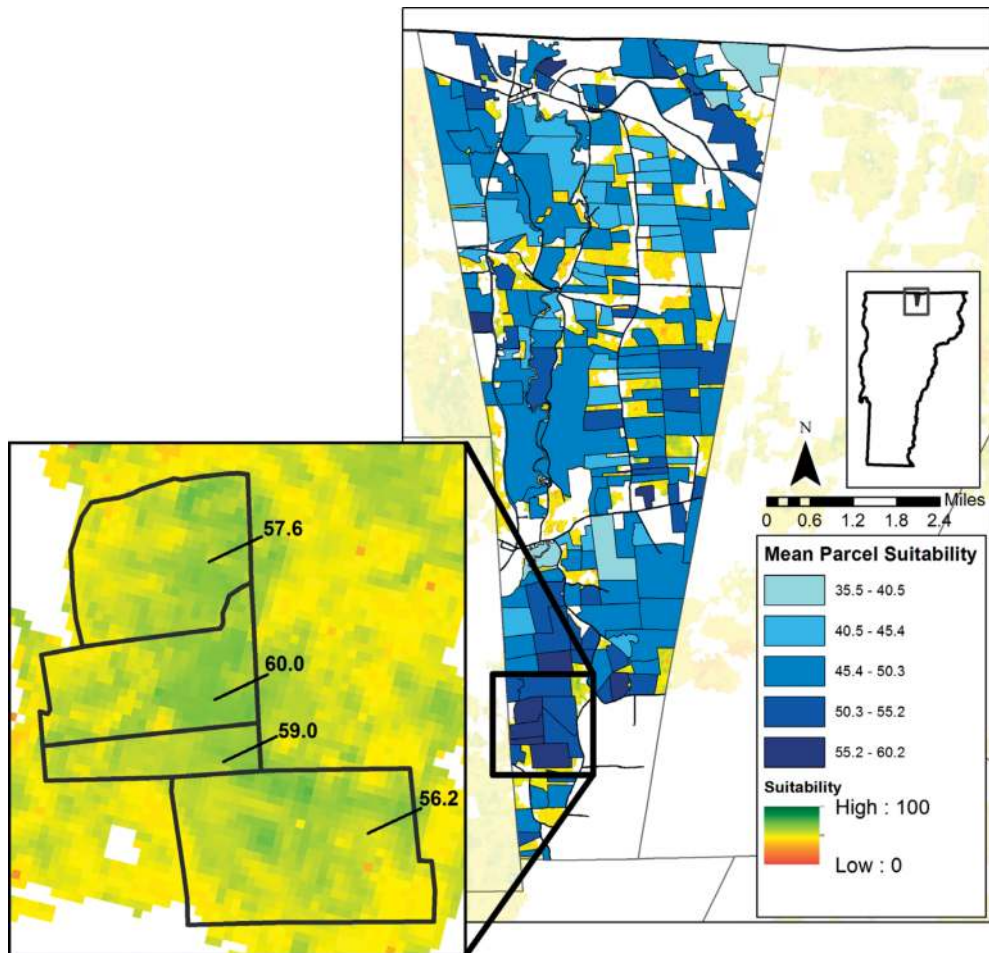


Figure 7. Mean suitability for parcels >25 acres (10.1 ha) for the town of Troy, Vermont, and a close-up look at suitability rankings on four parcels with high means (inset).

State Forest Planner (Hemlock Focus)

Objectives	Weight	Desirability setting
Sugar maple basal area	0	
Hemlock basal area	50	High desirable (1)
Sugar maple stress	0	
Hemlock susceptibility	50	Low desirable (-1)
Forest conversion risk	0	
<i>Sum</i>	<i>100</i>	

Table 4. Customized objective weights and desirability settings to identify high hemlock abundance and low HWA risk across the area of interest.

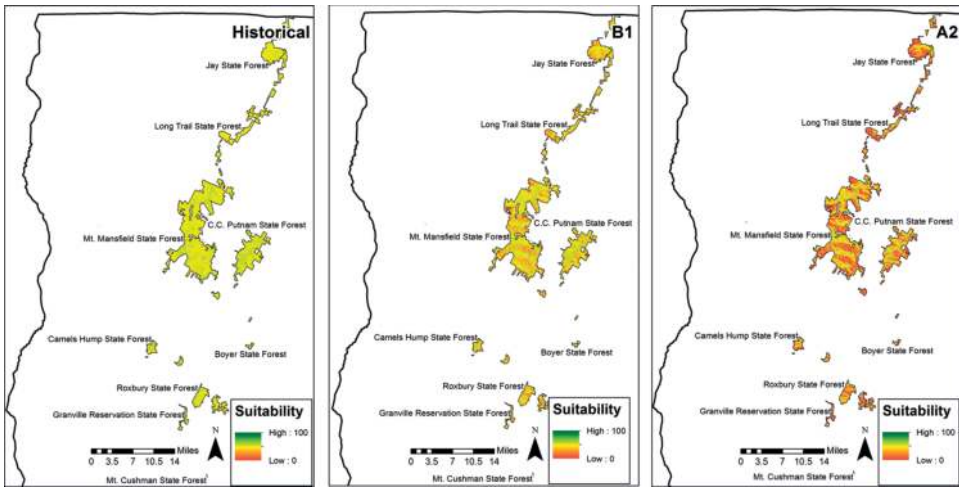


Figure 8. Output maps of weighted suitability for every 30 m pixel on state-owned parcels across the selected study area demonstrate how relative suitability for hemlock refugia differs geographically and under various climate change scenarios.

The State Forest Planner has used Vermont's state forest boundaries as the area of interest and as the unit for generating summary statistics and has set a suitability threshold of 60. Opting for summary data in chart rather than table form, the State Forest Planner can see which of their forests are ideally suited for hemlock management, and quantify which are most likely to decrease in suitability under a changing climate (**Figure 9**).

In this example, Camels Hump State Forest has the highest proportion of its area above the 60th percentile suitability threshold under current climate conditions, while Mt. Mansfield has the highest total area. Considering the proportion of suitable land, two smaller forests rank highest under the climate change scenarios, with 12.9% of Boyer State Forest above the threshold under the low emission scenario and 4.7% of Mt. Carmel State Forest above the threshold under the high emission scenario. But in terms of absolute area, Mt. Mansfield and CC Putnam State Forests provide the largest base of suitable landscape. Comparison of the climate scenarios also helps to identify how vulnerable hemlock stands in the different forests may be to climate change. For example, the proportion of suitable hemlock stands in the West Rutland State Forest changes modestly between the climate norms and B1 scenarios. In contrast, the Camels Hump State forest loses almost half of its suitable hemlock under the B1 scenario.

These maps and data give the Forest Planner a set of criteria that they can use to evaluate against other factors, such as funding, staff capacity, and institutional opportunities for experimentation. The forest planner can take these results and analyze trade-offs to target a smaller forest as a demonstration project or spreading management efforts across a larger land area while considering the long-term effects of climate on their hemlock management

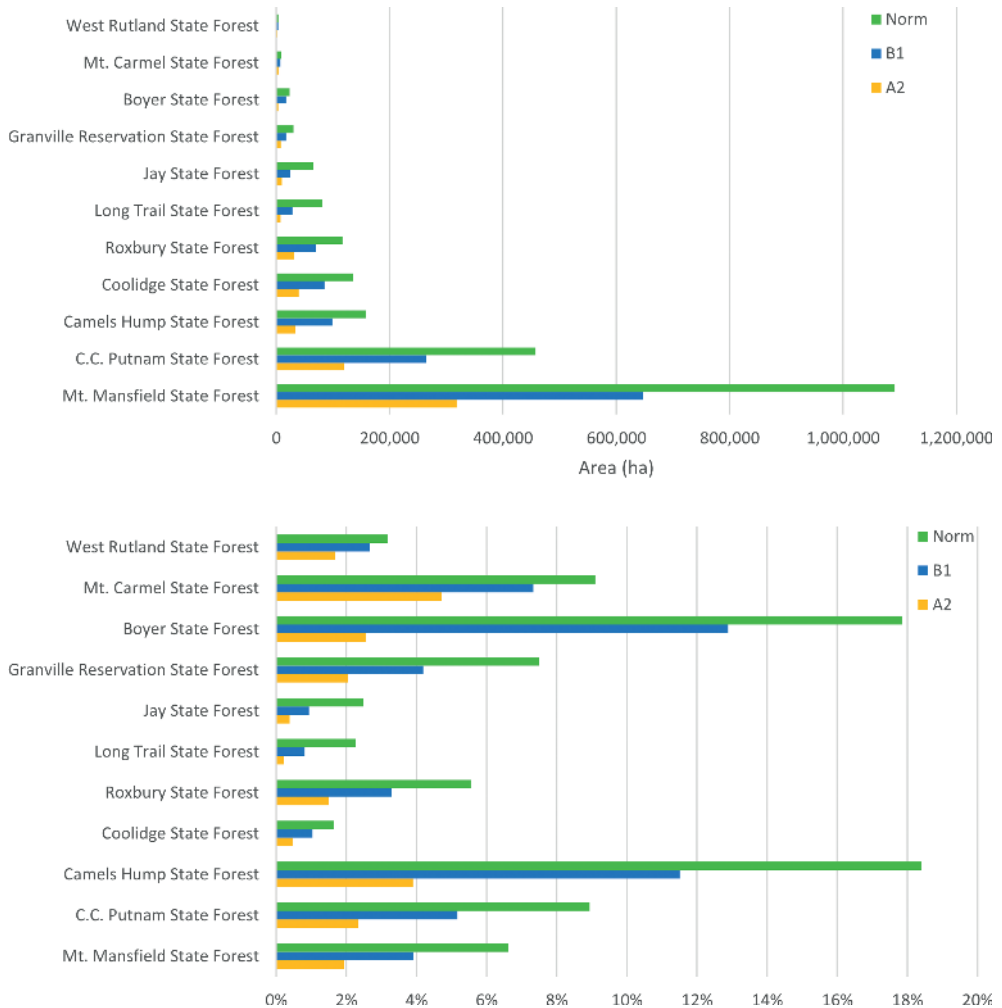


Figure 9. Graphical output summarizes the total area (top) above the specified suitability threshold for the areas of interest (VT State forest lands) under three different climate scenarios. This information can also be summarized as percent of total area (bottom), which helps to emphasize the importance of smaller parcels.

goals. This information provides necessary information to target management activities on the ground and justification for management decisions.

4.3. Case study 3: climate action advocacy group

Presenting before the State Legislature, this organization is looking to demonstrate the potential severity of climate change impacts on the state's largest natural resource: its forests.

Specifically, they want to quantify how our ability to maintain sugar maple and eastern hemlock stands across the state is likely to change under various climate projections, with all management objectives equally weighted as described in **Table 5**. They are particularly interested in private lands because Vermont’s forests are 80% privately owned, and they want legislators to provide new incentives for landowners to implement climate-resilient management strategies for these important species.

Area of interest: Vermont private lands.

Input empirical models: Percent Hemlock Basal Area, Percent Sugar Maple Basal Area, Sugar Maple Stress Index Model, Forest Conversion Model, Hemlock Risk Model.

Ancillary data layers: Conserved lands, Vermont Protected Lands Database, Vermont Centre for Geographic Information. Last updated 2016.

Summarize by: State of Vermont.

Climate scenarios: Sugar Maple Stress and Hemlock Risk Models with inputs for Historic norms, A2 (high emissions), and B1 (low emissions) scenarios.

Output maps of this objective prioritization that equally weight all available management objectives demonstrate the potential impacts of climate change on the region’s sugar maple and hemlock resource (**Figure 10**). The user has chosen nonpublic, nonconserved lands as their area of interest to capture the private ownership that dominates in VT, and selected to generate summary statistics for the entire region.

First, it is interesting to note how the geographic patterns of suitability scores vary significantly for this combined outcome weighting (emphasizing both sugar maple and hemlock) compared to an emphasis only on sugar maple in Case Study 1 and only on hemlock in Case Study 2. This highlights the importance of targeting specific management objectives, including allowing for a complex combination of multiple management objectives. The decisions that result from these differential weightings can vary widely.

Advocacy Group (Climate Change Focus)		
Objectives	Weight	Desirability setting
Sugar maple basal area	20	High desirable (1)
Hemlock basal area	20	High desirable (1)
Sugar maple stress	20	Low desirable (-1)
Hemlock susceptibility	20	Low desirable (-1)
Forest conversion risk	20	Low desirable (-1)
<i>Sum</i>	<i>100</i>	

Note that the key information desired from this case is a comparison of how climate impacts our ability to maintain suitable habitat for all listed management objectives.

Table 5. Customized objective weights and desirability settings to integrate across all management objectives.

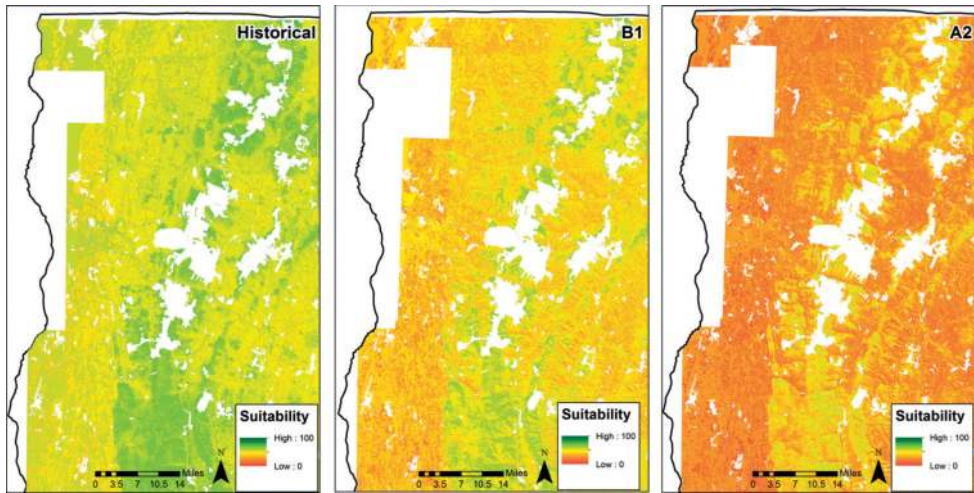


Figure 10. Output maps of weighted suitability for every 30 m pixel on private owned parcels with either hemlock or sugar maple present demonstrate how relative suitability differs geographically and under various climate change scenarios for this customized analysis equally weighting all available management objectives.

Second, it is striking how drastically overall suitability declines under both low and high emission scenarios (Table 6). Across the study area, suitability drops considerably, with a study-wide mean of 56.3 under historical norms dropping to 44.3 under low emissions and 28.8 under high emissions. This drop is particularly pronounced along the Lake Champlain Valley where a large portion of Vermont’s population is located.

Using the current suitability values as a baseline representing the current “standard” of forest health, our hypothetical climate advocate stakeholder group could quantify the proportion of the region’s forest lands that fall more than a standard deviation below current “mean/baseline” suitability. This provides a tangible value to present to policy makers they hope to influence to promote climate policy. In this management prioritization scenario, the user can say that 65.6% of the region’s forest will become less suitable to sustaining a healthy sugar maple and hemlock forests under a low emission scenario. They can further demonstrate that 95.2% of the region’s forest will become less suitable under a high emission scenario.

Climate scenario	Mean suitability	Maximum suitability	Range in suitability
Historical norms	56.3	79.9	55.6
B1 – low emissions	44.3	73.3	58.5
A2 – high emissions	28.8	65.6	59.7

Table 6. Summary statistics of suitability scores across the entire study area demonstrate how suitability can be expected to change under various climate scenarios.

With these substantial drops in suitability, the advocate can make an argument that Vermont will face significant challenges in maintaining hemlock, and maple species on private lands under even generous climate change scenarios, arguing for proactive efforts by the state to encourage landowners to take action. This may include implementing management efforts on private lands directed at managing forests for resilience and resistance. Or it could be used to justify policy changes to limit or mitigate greenhouse gas emissions. The maps, summary statistics, and underlying science provide the advocate with a set of materials to take to a lobbying session or public hearing where they can advocate for better protections and management of important forest resources across the state.

5. Conclusions

One challenge that many natural resource managers face is the uncertainty of climate change and the effects that large-scale changes will have on resources at a parcel- to landscape scales. With the ability to explore different climate change outcomes for a particular set of objectives, managers can find bounds to their expectations, lowering the barrier to incorporating climate change into management planning.

While many forest decision support tools exist, there is a notable gap in the ability to combine projections of climate change with current ecosystem models, linked to discrete forest management objectives in a flexible way pertinent to their scale and extent of interest. This puts the Future Forests Geo-Visualization Decision Support (**FForGeoVDS**) tool in a particularly good position for adoption and use to a broad audience of stakeholders. Because outputs include quantitative metrics to identify locations across a property or landscape where various management objectives are most likely to be met, the possibility of selecting different locations is highly dependent on objective weightings. This may prove particularly useful for conservation efforts, where resources to conserve targeted properties are limited, but conservation goals are complex.

The case studies we have presented here outline three potential uses for this tool. The ability to refine and target areas meeting multiple objectives, as in the case of the land trust director, or the ability to compare the suitability of a short list of state-owned properties, as in the case of the state forest planner, provides powerful new ways of combining scientific models, GIS data layers, and climate projections to generate detailed maps, useful summary statistics, and motivating graphics. However, we expect to see a more diverse range of users as the decision tool is refined and additional empirical models are included (e.g., wildlife occupancy, recreational patterns, carbon storage, etc.). This increases the number of management objectives one can consider and thus the robustness of the tool.

The **FForGeoVDS** research team has actively engaged with land managers and decision makers from nonprofits, state and federal natural resource departments and agencies, and advocates to understand what questions they face and what outputs and supporting material a decision support system focused on climate change and forests should provide. These

working sessions have proven invaluable in the development and design of the tool. Because of the diverse nature of these stakeholder groups, initial feedback has ranged from a desire for more detail, flexibility and complexity, to a desire for more simplistic approaches. This exemplifies the importance of continuous interaction with stakeholders to find the best fit for the most users and the need for continual updates, additions and increased functionality to the tool itself.

Acknowledgements

This work is funded by the McIntire-Stennis Cooperative Forestry Research Program, a USDA National Institute for Food and Agriculture program for forestry and natural resources research. The development of the Future Forests Geo-Visualization Decision Support (**FForGeoVDS**) tool has been led by research scientists at the University of Vermont including: Carol Adair, Anthony D'Amato, Theresa Donovan, Clare Ginger, Gary Hawley James Murdoch, Paul Schaberg, and William Valliere. The **FForGeoVDS** tool would not be possible without the integration of empirical models from researchers outside our research group. The case studies presented here include the use of empirical models developed by Alison Adams, Lesley-Ann Dupigny-Giroux, David Gudex-Cross, William Livingston, and Evan Oswald. We are also grateful to the many stakeholders from the management and forestry communities who have helped in the design of the **FForGeoVDS** tool, particularly our partners at the VT Agency of Natural Resources Department of Forests, Parks and Recreation, the US Forest Service, and many planners, practitioners, and nonprofit collaborators who have generously donated their time to this effort.

Author details

Jennifer Pontius^{1*} and James Duncan²

*Address all correspondence to: jennifer.pontius@uvm.edu

1 Rubenstein School of Environment and Natural Resources and US Forest Service Northern Research Station, University of Vermont, Burlington, VT, USA

2 University of Vermont, Vermont Monitoring Cooperative, Burlington, VT, USA

References

- [1] Korschgen C, Knutson M, Fox T, Holland-Bartels L, Dehaan H, Theiling C, Rohweder J, Kenow K, Leake L, Will T. Natural Resource Assessment and Decision Support Tools for Bird Conservation Planning. Albany, CA: Department of Agriculture, Forest Service, Pacific Southwest Research Station. PSW-GTR-191; 2005

- [2] Reynolds K, Twery M, Lexer M, Vacik H, Ray D, Shao G, Borges J. Decision-support systems in natural resource management. In: Burstein H, editor. *Handbook on Decision Support Systems 2*. Berlin: Springer; 2011. p. 800
- [3] Keenan RJ. Climate change impacts and adaptation in forest management: A review. *Annals of Forest Science*. 2015;**72**(2):145-167
- [4] Rammer W, Schauflinger C, Vacik H, Palma JH, Garcia-Gonzalo J, Borges JG, Lexer MJ. A web-based ToolBox approach to support adaptive forest management under climate change. *Scandinavian Journal of Forest Research*. 2014;**29**(sup1):96-107
- [5] Schmoldt DL, Kangas J, Mendoza GA. Basic principles of decision making in natural resources and the environment. In: *The Analytic Hierarchy Process in Natural Resource and Environmental Decision Making*. Netherlands: Springer; 2001. pp. 1-13
- [6] Mardani A, Jusoh A, Nor K, Khalifah Z, Zakwan N, Valipour A. Multiple criteria decision-making techniques and their applications—A review of the literature from 2000 to 2014. *Economic Research-Ekonomska Istraživanja*. 2015;**28**(1):516-571
- [7] Malczewski J, Rinner C. Development of GIS-MCDA. In: *Multicriteria Decision Analysis in Geographic Information Science*. Berlin Heidelberg: Springer; 2015. pp. 55-77
- [8] Hajkowicz SA, McDonald GT, Smith PN. An evaluation of multiple objective decision support weighting techniques in natural resource management. *Journal of Environmental Planning and Management*. 2000;**43**(4):505-518
- [9] Matthies M, Giupponi C, Ostendorf B. Environmental decision support systems: Current issues, methods and tools. *Environmental Modelling & Software*. 2007;**22**(2):123-127
- [10] Pechanec V, Brus J, Kilianová H, Machar I. Decision support tool for the evaluation of landscapes. *Ecological Informatics*. 2015;**30**:305-308
- [11] Rudner M, Biedermann R, Schröder B, Kleyer M. Integrated grid based ecological and economic (INGRID) landscape model—A tool to support landscape management decisions. *Environmental Modelling & Software*. 2007;**22**(2):177-187
- [12] Andrienko G, Andrienko N, Jankowski P, Keim D, Kraak MJ, MacEachren A, Wrobel S. Geovisual analytics for spatial decision support: Setting the research agenda. *International Journal of Geographical Information Science*. 2007;**21**(8):839-857
- [13] Twery MJ, Rauscher HM, Bennett DJ, Thomas SA, Stout SL, Palmer JF, Hoffman RE, DeCalesta DS, Gustafson E, Cleveland H, Grove JM. NED-1: Integrated analyses for forest stewardship decisions. *Computers and Electronics in Agriculture*. 2000;**27**(1):167-193
- [14] Ekbia HR, Reynolds KM. Decision support for sustainable forestry: Enhancing the basic rational model. In: Reynolds KM, Thomson AJ, Kohl M, Shannon MA, Ray D, Rennolls K, editors. *Sustainable Forestry: From Monitoring and Modelling to Knowledge Management and Policy Science*. Cambridge, MA: CABI; 2007

- [15] Fontes L, Bontemps JD, Bugmann H, Van Oijen M, Gracia C, Kramer K, Lindner M, Rötzer T, Skovsgaard JP. Models for supporting forest management in a changing environment. *Forest Systems*. 2010;**19**(special):8-29
- [16] Vacik H, Lexer MJ. Past, current and future drivers for the development of decision support systems in forest management. *Scandinavian Journal of Forest Research*. 2014;**29**(sup1):2-19
- [17] Gudex-Cross D, Pontius J, Adams A. Enhanced forest cover mapping using spectral unmixing and object-based classification of multi-temporal Landsat imagery. *Remote Sensing of Environment*. 2017;**196**:193-204
- [18] Adams A, Pontius J, Galford G, Gudex-Cross D. 45 years of forest conversion in the Northeast: historical patterns and future projections. *Canadian Journal of Forest Research*. In review
- [19] Oswald E, Pontius J, Dupigny-Gireaux LA, Wilmot S, Rayback S. The complex relationship between climate and sugar maple health: Climate change implications for a key northern hardwood species. *Forest Ecology and Management*. In review
- [20] Livingston WH, Pontius J, Costanza KK, Trosper S. Using changes in basal area increments to map relative risk of HWA impacts on hemlock growth across the Northeastern USA. *Biological Invasions*. 2017;**19**(5):1577-1595
- [21] Edwards W. *Social Utilities, Engineering Economist, Summer Symposium Series*. London, UK: Taylor & Francis. 1971. p. 6
- [22] Goodwin P, Wright G. *Decision Analysis for Management Judgment* 5th ed. Hoboken, NJ: John Wiley and Sons; 2014

