

An agent-based modelling approach to project future habitat suitability for Northern Spotted Owl in Central Oregon

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Abstract: Wildfires remain a major threat to Northern Spotted Owl habitat in Central Oregon, and there is an urgent need for tools to support the development of effective conservation planning strategies. We describe the managed forest ecosystem in Central Oregon as a coupled human and natural system and apply the agent-based modelling framework ENVISION for quantifying the integrated effects of wildfires, vegetative succession, and human decisions regarding forest and fire management on the suitability of owl habitat. Our simulation results show that ENVISION is suitable for the simulation of complex system feedbacks and links over different spatial and temporal scale levels. It is applicable to generate interdisciplinary insights for policy research and application planning that cannot be gained from ecological or social research alone. However, modelling approaches such as ENVISION require a better empirical foundation in order to be able to utilize their full potential for the development of effective conservation planning strategies.

Keywords: ENVISION; agent-based modelling; Northern Spotted Owl (*Strix occidentalis caurina*); habitat suitability index.

1 INTRODUCTION

The implementation of the Northwest Forest Plan, developed to sustain biological diversity in the Pacific Northwest [USDA Forest Service and USDI Bureau of Land Management 1994], led to a sharp decline in Northern Spotted Owl (*Strix occidentalis caurina*, NSO) habitat loss rates [Ager et al. 2007]. Yet, management efforts, such as fire suppression, may lead to increased risk of high severity fires [Pyne 1997]. Courtney et al. [2004] report that wildfires cause 75% of the disturbance-related NSO habitat losses. As a result, significant research effort has focused on the relationship between wildfires, vegetative succession, and NSO conservation (e.g. Ager et al. [2007], Kennedy and Wimberly [2009]). Much of this effort has focused on the relationship between wildfires and NSO habitat. Only a few studies explicitly address the development of effective conservation planning strategies. However, Spies et al. [2006] highlight the need to evaluate landscape level strategies to sustain NSO habitat and promote forest resilience under disturbances. The concept of coupled human and natural systems [Liu et al. 2007] provides a framework for describing and analysing highly complex forest ecosystems. According to Liu et al. [2007], coupled human and natural systems are integrated systems in which people interact with natural components. Agent-based modelling approaches have been widely used as tools to represent people, behaviour and decision-making processes in these systems [Rounsevell et al. 2012a, Parker et al. 2003, Matthews et al. 2007]. Agent-based modelling provides a framework for the simulation of complex decision making processes [Rounsevell et al. 2012b] and allows for artificial experiments to explore system behaviour, where real life experi-

ments are not possible. As a result, they are suitable to evaluate policies, provide input to planning processes, and increase our understanding of how policies might affect land uses and the provision of goods and services.

In this paper, we describe the managed forest ecosystem in Central Oregon as a coupled human and natural system. We outline an agent-based model that quantifies the integrated effects of wildfires, vegetative succession, and human decision making processes with respect to forest management and the resulting effects on the conservation and the formation of suitable NSO habitat. Specifically, we used the ENVISION framework [Bolte et al. 2007] configured with a set of new plug-ins to dynamically simulate the spatial extent of wildfires, vegetative succession, and NSO habitat suitability. A set of forest management strategies was specified and tested for their effectiveness in conserving suitable NSO habitat in a study area (288 km²) in Deschutes County in Oregon, USA.

2 MATERIALS AND METHODS

2.1 Modelling System

The ENVISION framework was designed for the development and analysis of spatially explicit landscape change simulations [Bolte et al. 2007]. ENVISION provides a pre-defined architecture within a general paradigm incorporating actors, decision rules, spatially explicit landscape representations, landscape feedbacks, and adaptation processes.

Actors. A set of actors operates on the landscape. Actors can be based on individuals, collections of individuals (e.g. institutions), or can be abstractions with no real world counterpart. The behaviour of actors is specified by their value system. Based on this system, actors select rules for decision making, which constrain their behaviour. The application of a decision rule by an actor results in changes of landscape attributes.

Landscape. A landscape in ENVISION consists of a set of spatial containers (polygons) that specify the level of decision making by actors. These spatial containers are called integrated decision units (IDUs). For each IDU, information on landscape characteristics (e.g. land cover) and attributes required for decision making (e.g. ownership) are specified. Each IDU is related to an actor. The actor has decision authority over its IDU and, hence, makes decisions about the management of this part of the landscape.

Decision rules. Decision rules are applied by actors to accomplish land management decisions. They represent plans of action for accomplishing a desired outcome [Lackey 2006]. Besides private land management decisions, the rules capture incentives and other strategies given by public agencies in order to regulate society's demands for ecological goods and service. They contain information about site attributes defining the spatial domain of application of the rule and goals the policy is intended to accomplish.

Decision making process. The decision making process of an actor is formulated as a stochastic multi-criteria model considering multiple factors in order to determine, which decision rule is selected and applied by an actor. The considered factors are the consistency of actor values and intentions related with the decision rule (based on the degree of self-interest), the consistency of actor values and global scarcity measures (based on the degree of altruism), and the intensity of interaction of an actor with other actors that successfully applied a specific decision rule.

Metaprocess. A metaprocess represents a feedback that introduces high-level behavioural change to the human and natural system. The behaviour of an actor is specified by its value system and its connection to other actors. This is where the meta-process takes effect: it changes actor values and interaction between actors, based on the output of the landscape evaluator, as a response to societal measures of scarcity. This allows actors to adapt their behaviours based on landscape feedbacks and interaction with other actors.

Landscape evaluator. This component evaluates the landscape with metrics that quantify a specific type of system production with relevance to actor decision mak-

ing. Landscape evaluators are used to indirectly introduce feedbacks into the system by quantifying the actors' impact on the landscape as well as by influencing actor behaviour via metaprocesses.

Autonomous process. An autonomous process represents changes in landscape attributes that are not directly caused by the application of decision rules, i.e. actor decision making. These processes change the landscape periodically.

ENVISION, as an alternative futures model, was designed to formulate knowledge and provide insights on system behaviour. It combines intrinsic complexity with long timeframes and focuses on the simulation of land-use intensity changes. This, in conjunction with limited data availability, makes traditional validation approaches unsuitable. Hence, our focus is the provision of reasonable estimates of the bounds of system behaviour and not the prediction of specific outcomes. A detailed description of ENVISION is given in [Bolte et al. 2007]; examples of model application are given by Guzy et al. [2008] and Hulse et al. [2009]. More information on the framework as well as a downloadable version of ENVISION are available at <http://envision.bioe.orst.edu/>.

2.2 Landscape

The study area is located on the east slope of the Cascade Range in Deschutes County in Oregon, USA (Figure 1). The study area covers a geographic area of 288 km². The geographic area of IDUs, which are based on a combination of tax lots and land-use data, ranges from 0.06 ha to 9.48 ha; the average size of IDUs is 3.34 ha. The study area was chosen because it represents a good cross section of landscape characteristics of Central Oregon with relevance to the subject matter of the analysis. It extends from the crest of the Cascade Range with its cold, wet sub-alpine forest types to the very dry shrub-steppe with less than 300 mm mean annual precipitation. Stretching from west to east, dominant forest types are high elevation conifers, mixed conifers and lodgepole pine, ponderosa pine, and junipers. The forest type that covers the largest part of the study area is ponderosa pine.

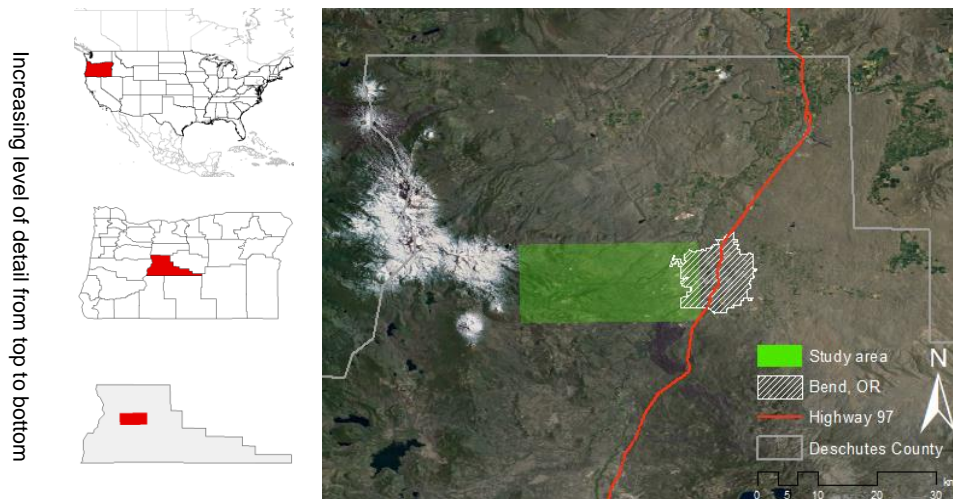


Figure 1. Study area, located near Bend in Deschutes County in Oregon, USA.

In the eastern portion of the study area is the city of Bend. Bend is the largest city in Central Oregon with rural, residential, and urban reserve zoning. The US Forest Service manages the largest share of forest lands in the study area (60 %). Other landowners include private industrial (15 %) and private non-industrial (25 %), with the latter located primarily in the eastern part of the study area.

2.3 Actors and Decision Rules

Our study considers three different actor groups: (i) non-industrial private forest owners (NIPF), (ii) industrial private forest owners (IPF), and (iii) the US Forest

Service forest managers (USFS). Each actor group has a set of decision rules, i.e. forest management strategies. We implemented two decision rules for IPF based on rotation length: harvest on a harvest interval of 40 or 80 years. Decision rules for NIPF base on existing equations characterising NIPF harvest and thinning activities as functions of landscape characteristics such as slope and stand basal area [Kline and Azuma 2007]. The application probabilities for harvesting and thinning are calculated for each IDU in each time step. The management strategy with the highest probability of application is chosen, and eventually applied by the NIPF. For USFS, two decision rules were implemented: one decision rule for conservation and one harvest decision rule with a rotation length of 40 years. The application of the harvest decision rule is limited to areas that were not assigned as conservation areas in previous time steps. The USFS decision rules were implemented with an expansion function; in case one of these policies is chosen for application on an IDU, the surrounding area (up to 15 ha) is also harvested or categorized as conservation area. All policies have a score, which defines their suitability for conservation of NSO habitat. All harvesting policies, except the ones with 80 years rotation length, have low values, whereas thinning, harvest intervals with 80 years rotation length, and conservation have high values for NSO habitat conservation.

2.4 Autonomous Processes

Dynamic vegetation modelling. In ENVISION each IDU on the landscape belongs to a vegetation state class that is characterized by a unique combination of dominant species (cover type), structure (structural stage), and age class. In the state class-and-transition modelling approach, a state class is moved from one state class to another based upon pre-defined pathways. The method in which the state class is selected depends upon whether the transition is due to natural succession or is a result of a disturbance on the landscape. Natural succession is determined both probabilistically and deterministically, where disturbance types like harvest, fire, thinning, mechanical mowing, and restoration are handled through different disturbance handlers within ENVISION.

Within ENVISION natural vegetative successions are both probabilistically and deterministically determined by models developed specifically for the study area by the Integrated Landscape Assessment Project (ILAP)¹. The ILAP models characterize each vegetation state class by cover type, structural stage, and age class. For probabilistic transitions a method similar to that used in the Vegetation Dynamics Development Tool is employed [ESSA Technologies Ltd. 2007]. For deterministic transition, a new state class is selected when the number of time steps a state class remains in the defined age class exceeds the upper bounds of that age class.

Dynamic fire modelling. Spatially explicit simulation of wildfires is performed by a straightforward ENVISION “plug-in”, which follows a probabilistic approach. The calculation of wildfires is carried out on the IDU level. Applying pre-specified values for maximum number of ignitions per year, mean fire size, and burn threshold, the disturbance due to wildfires is calculated. Interdependencies between neighbouring IDUs are considered. Based on mean fire size, ignition of neighbouring IDUs takes place if the burn index of an IDU exceeds the burn threshold. The burn index of an IDU is derived from a simple fuel model based on land-use/land-cover type. If sufficient suitable IDUs are available (with regard to their burn index), contagion is solely constrained by the fire size drawn from a distribution. The output of the fire model directly affects vegetation characteristics.

2.5 Landscape Evaluator

Habitat suitability index. In this study, we use a Habitat Suitability Index (HSI) based on the work of McComb et al. [2002] to quantify the quality of habitat for Northern Spotted Owl (*Strix occidentalis caurina*). The HSI ranges between 0 and 1 and is a composite of nest site score (HSIN) and landscape (forage area) score

¹ <http://oregonstate.edu/inr/ilap>

(HSIL). The HSIN is defined on a 90 m grid cell, whereas the HSIL is defined on an area within 1 km of a focal 90 m grid cell. The composite HSI score is calculated as:

$$HSI = \sqrt[3]{HSIN^2 * HSIL} \quad (1)$$

The score for HSI is 0 if the habitat is east of Highway 97, which is outside the range of the owl, or if the potential vegetation type (PVT) of a grid cell is not Mixed Conifer (moist), Mixed Conifer (cold/dry) or Western Hemlock, which are forest types that are used by the owl for nesting and roosting.

A HSIN of greater than 0 is possible only if multiple canopy layers are present at a grid cell. The HSIN is set to 1 if canopy cover on a grid cell is $\geq 60\%$, if the stem size is ≥ 40 cm and if the PVT is Mixed Conifer (moist), Mixed Conifer (cold/dry) or Western Hemlock. The HSIN is set to 0.5, if canopy cover on a grid cell is between 40 % and 60 % and if the stem size is between 25 cm and 39 cm. Furthermore, the HSIN is set to 0.5 for canopy cover $\geq 60\%$, and stem size between 25 cm and 39 cm or canopy cover between 40 % and 60 % and stem size ≥ 40 cm. For all other situations, the HSIN is set to 0.

The HSIL is set to 1 if canopy cover within 1 km of the focal grid cell averages above 60 % and if the aggregate cover of the PVT classes Mixed Conifer (moist), Mixed Conifer (cold/dry), Western Hemlock, and Mountain Hemlock is greater than 60 %. The HSIL is set to 0.5 if canopy cover within 1 km of the focal grid cell averages above 40 % and if the aggregate cover of the PVT classes Mixed Conifer (moist), Mixed Conifer (cold/dry), Western Hemlock, and Mountain Hemlock is greater than 30 %. For all other situations, the HSIL is set to 0.

In order to assess the impact of actor decisions on the landscape level, the average HSI for the entire study area is calculated and considered as a measure to quantify the success with regard to suitable NSO habitat.

2.6 Input Data

In this study, different datasets were used to prepare the IDU shapefile and specify the base year conditions for the landscape attributes. The definition of IDUs in this study is based on a combination of tax lot data provided by the Deschutes County Information Technology Department and information on land-use and land-cover. The spatial configuration of IDUs and the corresponding owner remains static over the course of the simulation. The calculation of HSI for NSO is based on information on PVT, canopy cover, stem size, and number of canopy layers. For the base year of the simulation, this information is specified on the IDU level and is derived from the LEMMA IMAP GNN dataset [Ohmann et al. 2011]. For subsequent time steps, the information is updated via the vegetation modelling autonomous process (see section 2.4).

2.7 Study Setup

The analysis presented in this study is based on three different scenarios. The scenarios do not reflect different habitat management strategies, but were chosen to allow an analysis of the effect of the different processes implemented in ENVISION on the simulation results. In the first scenario, we do not include any human intervention, but examine the combined effect of vegetative succession and wildfires on habitat suitability for NSO. We refer to this scenario as “ES” for Environmental System. In our second scenario “HES” (Human-Environmental System) we additionally consider human interventions, i.e. forest management. In this scenario, all actor groups and their corresponding decision rules are considered. In a third scenario, referred to as “FHES” (Feedback of HSI on the Human-Environmental System), we include the mean habitat suitability for NSO at the landscape level in order to consider the feedback effect of changes in HSI on the behaviour of the actor groups. In this scenario, in which all actor groups and corresponding decision rules are considered, we implement HSI calculation as a landscape evaluator, and choose the altruistic mode for actors, guiding the actor’s choice of management strategies.

This represents the human actor response to decreases in ecosystem services, i.e. provision of habitat, at the landscape level.

Base year for all simulations is 2007. The simulations are carried out with a yearly time step and cover a simulation period of 44 years (2007 – 2050). Modelling systems such as ENVISION that do not follow a deterministic modelling approach but incorporate stochastic elements, typically require multiple simulation runs in order to generate an envelope around potential outcomes [Rounsevell et al. 2012a]. In this study, we run 25 simulations for each scenario.

3 RESULTS

With an average area decrease² through 2050 of only 0.84 km² (± 1.43 km²), the ES scenario shows almost no loss in area with an HSI > 0. Even though 19.22 km² (± 1.72 km²) of suitable owl habitat is lost under ES due to stand replacing fires, the area loss is compensated for by vegetative succession. For HES, the area with an HSI > 0 decreases by 24.62 km² (± 1.00 km²) and for FHES, the area with an HSI > 0 decreases by 18.90 km² (± 2.32 km²). Area losses due to stand replacing fires for HES and FHES are in the same order of magnitude as for ES. Since HES and FHES also consider vegetative succession, the higher losses in suitable NSO area can be attributed to the application of forest management (e.g. harvesting).

A spatial representation of the HSI simulation results for the year 2050 is given in Figure 2. The largest collection of regions with an HSI > 0 is located in forests managed by the US Forest Service. An analysis of the decision rule applications of USFS shows that for HES the conservation decision rule was applied about 186 (± 7) times, whereas the harvest decision rule was applied about 657 (± 19) times. For FHES, conservation was applied 797 (± 16) times and the harvest decision rule was applied 442 (± 17) times. This shows the strong effect of the feedback effect included in FHES on the application of decision rules, geared by the landscape level HSI.

The results presented in Figure 3 support this finding. The conservation application rate for FHES shows an increase while the corresponding rate for HES shows no clear trend. The application rate of the harvest decision rule is decreasing under HES and FHES. In case of HES, this is related to a decrease in potentially suitable application area, for FHES this is related to an increasing application of the conservation decision rule.

4 DISCUSSION AND CONCLUSIONS

In this study, we applied the agent-based modelling system ENVISION to explicitly simulate the complex interactions in a coupled human and natural system. We examined environmental variables (habitat suitability for NSO), human variables (actor behaviour), as well as the linkages between the natural and human components

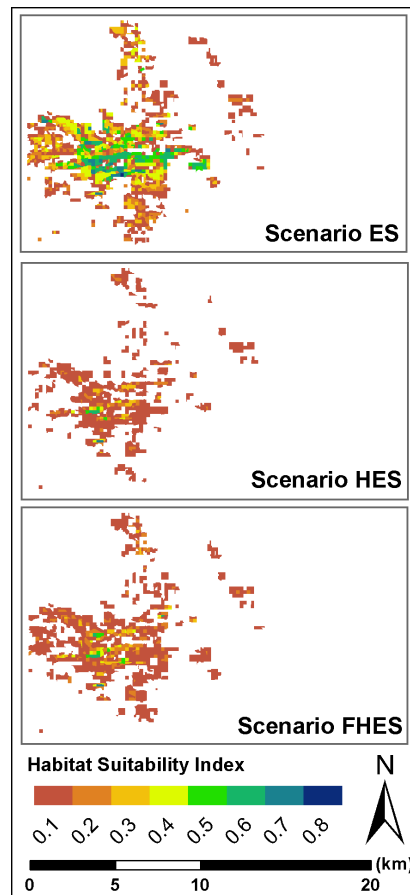


Figure 2. Simulation results for the mean habitat suitability index for the three scenarios (simulation end year 2050).

² All values referred to in this section are average values for the 25 simulation runs per scenario. The standard deviation is provided in parentheses.

considered in the modelling system (applications of policies). The mean habitat suitability index, a landscape-level indicator, was used to evaluate the success of decisions and to adapt actor decision making based on the success of prior decisions. Hence, we set up and applied a model that showed complex system feedbacks and links over different spatial and temporal scale levels. According to Rounsevell et al. [2012b] modelling these trans-scale processes is one of the challenges of modelling complex coupled human and natural systems.

We use only one landscape-level indicator (i.e. landscape evaluator) – the mean habitat suitability for NSO. Since landscape evaluators in ENVISION form the link between different spatial scales via the feedback effect of these evaluators on local decision making, future studies should include additional indicators. Besides indicators focusing on habitat characteristics such as landscape metrics [Uuemaa et al. 2009], indicators for other ecosystem services (e.g. timber production or amenity value of the landscape) should be taken into account in order to be able to consider trade-offs resulting from the application of different forest and fire management strategies.

An important characteristic of the present study is that we did not only consider decision rules for USFS forest managers, but also for other important actors in the study area. Since wildfires are a major threat for NSO habitat [Courtney et al. 2004], and since contagion of wildfires is not constrained by ownership, this factor was important to get a more comprehensive picture of the effect of human decision making on wildfires in the study area.

Nonetheless, there is a need to empirically ground modelling systems such as ENVISION with data about actual human behaviour [Rounsevell et al. 2012b]. For this purpose, data collected from landowner surveys will be fundamental, especially to set the boundary conditions of the model and identify plausible human behaviours. According to Rounsevell et al. [2012a], agent-based models are particularly suitable for the application of data from surveys of actor groups, since both agent-based models and data from surveys can be inherently qualitative.

Agent-based modelling approaches such as ENVISION are capable of representing feedbacks between human and natural systems that help to generate new insights on and better understanding of highly complex human and natural systems [Rounsevell et al. 2012a]. Thus, they can provide interdisciplinary insights for policy research and application planning that cannot be gained from ecological or social research alone [Liu et al. 2007] and support informed decision making. Still, current approaches require a better empirical foundation with data collected in actor surveys in order to be able to use their full potential.

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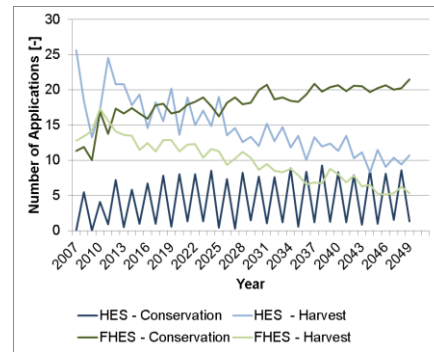


Figure 3. Development of the USFS decision rule applications over the simulation period.

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