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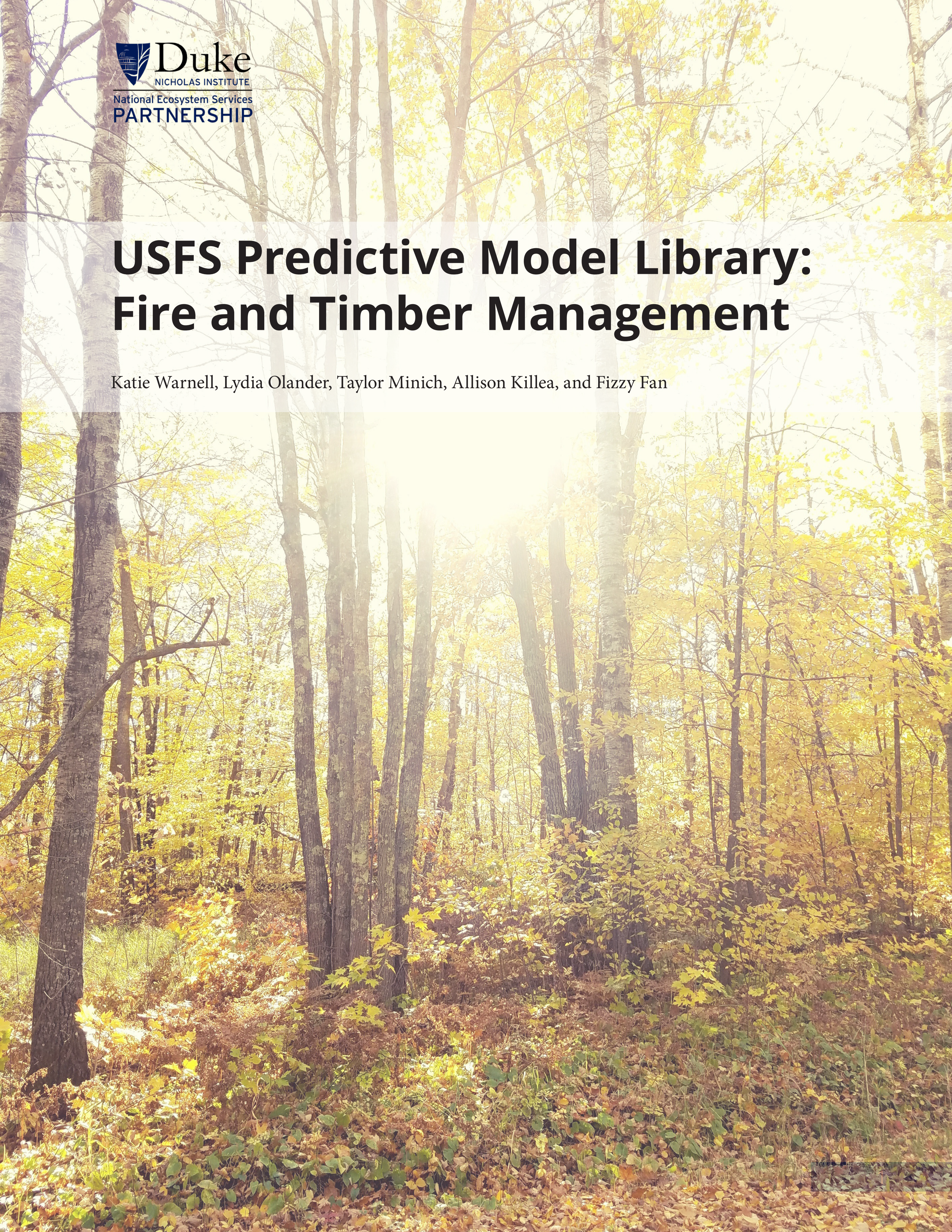

USFS Predictive Model Library: Fire and Timber Management

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CONTENTS

INTRODUCTION

The concept of ecosystem services has been formalized into U.S. Forest Service decision-making over the past decade in response to the 2012 Forest Planning Act and Agency regulations and directives, but many practical questions remain about how to do this most effectively. Many USFS decisions use scenarios to assess how different management approaches will meet different objectives and what the trade-offs might be. Often this is done using predictive models developed by the USFS. Some of the models commonly used by the USFS do not yet include many ecosystem services outcomes, but there are other predictive models designed for ecosystem services that might help fill such gaps. This project explores how these non-USFS models could be combined with existing USFS models to provide a fuller analysis of ecosystem services outcomes from different management scenarios. We used an ecosystem service conceptual model as a framework to examine the utility of currently available predictive models for quantifying the effects of fire and timber management on ecosystem services and socioeconomic outcomes.

ECOSYSTEM SERVICE CONCEPTUAL MODELS

Ecosystem Service Conceptual Models (ESCMs) are box-and-arrow diagrams that summarize the effects of an intervention, such as natural resource management, on ecological and social systems. Each model links changes in biophysical systems caused by an intervention to measurable socioeconomic, human well-being, and ecological outcomes. ESCMs assume that the intervention is successful and include all potentially significant outcomes for the intervention; not all outcomes will be relevant to each individual project, depending on location and environmental conditions.

The relationship of an intervention to an outcome (whether the restoration will have a positive or negative influence) often depends on the specific situation or is unclear due to multiple links (arrows) leading into an outcome that may have opposite effects. Thus, language like "increased" or "decreased" is not included in the models. These models are often used to consider management with or without an intervention or to compare different interventions.

Fire and Timber Management ESCM

The ESCM for Fire and Timber Management (Figure 1) was initially developed from literature and refined through a series of conversations with experts within and outside of USFS. Some experts provided feedback on the ESCM itself, while others reviewed the ESCM as part of a conversation about predictive models for relationships represented in the ESCM.

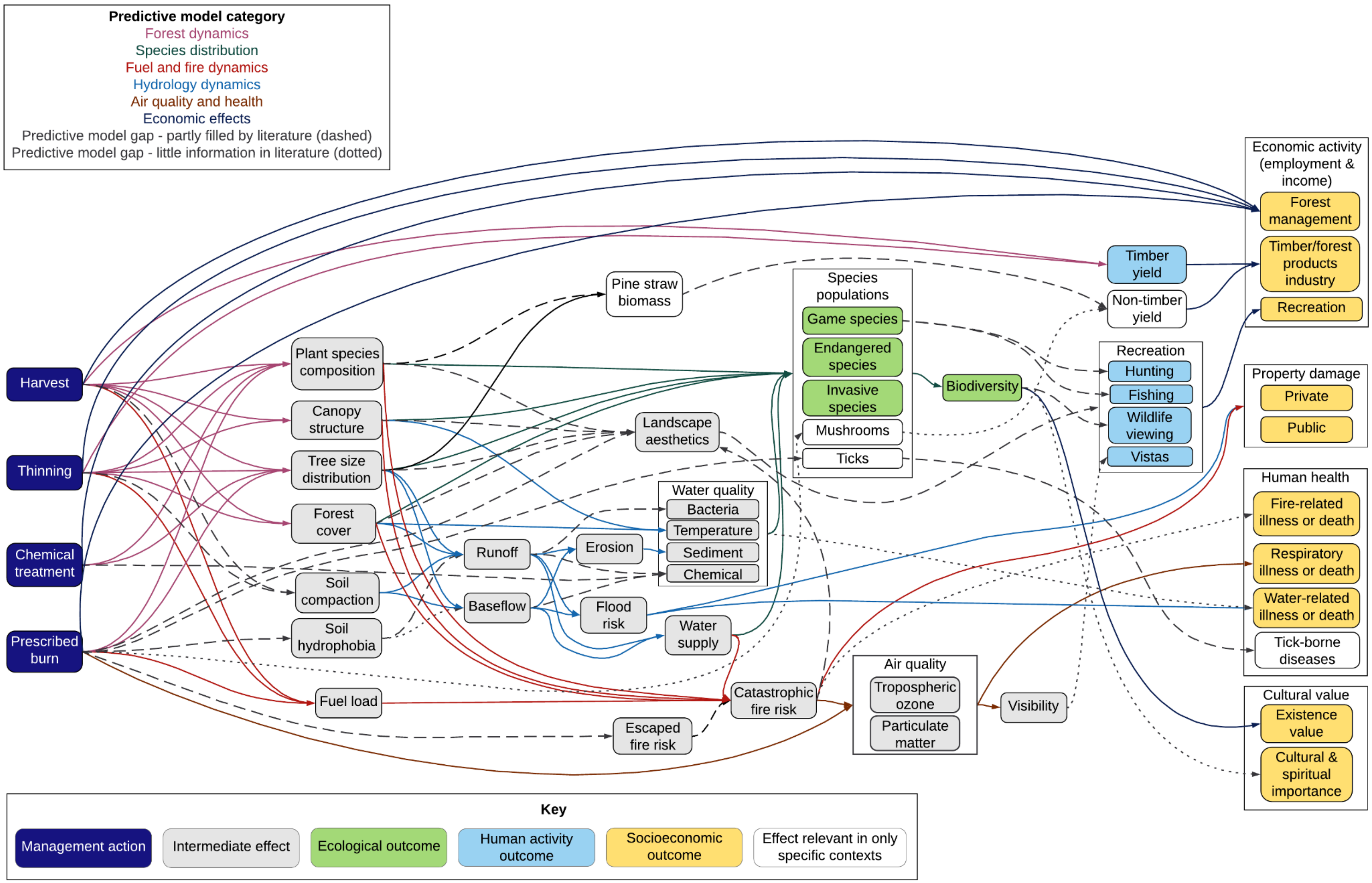
The ESCM for Fire and Timber Management includes four interventions:

- **Harvest** of timber for commercial sale
- **Thinning** vegetation to improve stands' commercial value or to manage fuel loads
- **Chemical treatment** to reduce undesirable vegetation types or to manage fuel loads
- **Prescribed burn** to manage fuel loads or shift tree species composition for harvest or habitat

The general version of the ESCM is available here. Additional information about the ESCM, including discussion of uncertain links and environmental factors that influence the interventions, can be found here.

The version of the ESCM below has links (arrows) color-coded by model category, corresponding with the predictive model summary tables (**page 6**). Where there are gaps in available predictive models, it also indicates whether there is information in the literature that can help to fill the gap (dashed black line) or a lack of information in the literature (dotted black line).

Figure 1: Ecosystem Service Conceptual Model for Fire and Timber Management on USFS Land with Predictive Model Information



PREDICTIVE MODELS FOR MANAGEMENT EFFECTS ON ECOSYSTEM SERVICES

Developing predictive or scenario modeling tools for ecosystem services often requires linking together a string of predictive models that lead from initial ecological changes, to how those changes affect people and, sometimes, to how people value those changes. Often, models across different types of ecological (e.g., hydrology, species, timber, fire) and social changes (e.g., recreational use, cultural connection, drinking or irrigation water use) must be connected together.

Error and Uncertainty in Predictive Modeling

Results of predictive models do not perfectly reflect what will actually occur in the system, since models are simplified versions of complex (and often not completely understood) processes (Uusitalo et al. 2015). Therefore, when using predictive models for management decisions, it is important to understand the error and uncertainty associated with the predictive model (Schmolke et al. 2010). In many cases, models have been validated by comparing their results with observed data that were not used in model development (see examples in the "evaluation" column in the predictive model summary tables). This can give an idea of the model's accuracy and error, but differences between the context in which the model was validated and the management context may make the model more or less accurate in the management context, and relevant observed data are often unavailable, especially in ecological contexts (Augusiak et al. 2014; Wenger and Olden 2012). The quality of input data available to run and calibrate the model also influences model accuracy (Sargent 2013).

Combining predictive models (i.e., using outputs from one model as input data for another model) raises additional issues related to model accuracy, uncertainty, and validation. Error and uncertainty from individual models can propagate through the combined model system (Laniak et al. 2013). This can make model results more challenging to use for management, especially if relevant observed data to test the accuracy of final model results are not available (Kelly et al. 2013). Bayesian network modeling, which integrates multiple predictive models to represent a complex system, can help to address this by incorporating uncertainty and variability of each individual model to create a probability distribution for each output variable (Borsuk et al. 2004).

Predictive Model Summary Tables

The following tables contain summaries of existing predictive models that can be linked together to quantify ecosystem services for timber and fire management. Predictive models can be fully developed tools designed for third-party use or equations described in scientific literature; the key defining feature is that they allow the user to estimate a change in a target variable (e.g., tree size, species population, fire intensity, jobs) from information about other variables thought to influence the target variable.

Predictive models were selected and summarized based on literature, model documentation, and conversations with modeling experts within and outside of USFS (see Acknowledgements). The Predictive Model Library is designed to provide a starting point for someone interested in building a model to run scenarios quantifying management effects on ecosystem services and people. It is not a comprehensive guide to using each predictive model, nor a combined model that is ready to run. Only the models that seemed most useful for quantifying effects on ecosystem services, based on literature and expert opinion, are included. In particular, we had a strong bias toward including models developed and used by the USFS, so that there is existing USFS expertise in running the models.

Predictive model summaries are presented in table format organized by topic. These topics correspond with the color-coded groups of relationships (arrows) in the conceptual model diagram (Figure 1):

Predictive model category	Summary table pages
Fuel and fire dynamics	8–11
Forest dynamics	12–13
Air quality and health	14–17
Hydrology	18–20
Economic effects	21–22
Species distribution	23

The summary for each predictive model includes the following sections:

Model name: Name of the model

Short description: Describes the processes the predictive model estimates and the context for which it was designed

Data requirements: Data required to run the model and common sources for these data, if available.

Model outputs: The variables and file types that the model creates

Connectivity to other models: How the predictive model can be connected with other predictive models (e.g., whether it can use other models' outputs for inputs, or if its outputs can be used as inputs for other models) and what data processing would be required to make those connections

Capacity required: Whether the model is freely available or needs to be purchased, what computing power is needed to run the model, and what level of expertise is needed to run the model

USFS contact or external resource: USFS staff familiar with the model who may be a resource to others interested in using it, if available, or model source

Evaluation: How the model's accuracy and validity has been evaluated, for example by comparing modeled results with observed data or through uncertainty analysis

Predictive Model Gaps

Some relationships (arrows) in the conceptual model do not have relevant predictive models. These predictive model gaps can be due to gaps in knowledge of the relationship or because the relationship is inherently difficult to quantify. These are shown as gray arrows in the conceptual model. Solid gray arrows indicate that there is some quantitative information about the relationship in the literature that could be used for rough quantitative estimates, but it does not address all aspects of the relationship or was developed for a context different from that of the relationship in the model. Dashed gray arrows indicate that there is little or no quantitative information about the relationship in the literature, often because the relationship has not been thoroughly studied or is inherently difficult to measure or quantify. Key predictive model gaps likely to be relevant to many USFS contexts include:

- The effects of harvest and thinning on soil compaction
- The effect of prescribed burns on soil hydrophobia, and subsequent effects on runoff and baseflow
- The effects of runoff and baseflow on water quality parameters including bacteria and chemical constituents
- The effects of catastrophic fires on property damage and human injury or death

A short discussion of each of the predictive model gaps is included after the predictive model summary tables (**page 24**).

Table 1. Predictive Model Summaries: Fuel and Fire Dynamics

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
FSim	FSim is a large-scale fire simulator. It models burn probabilities and fire size distribution based on fuel, topography, and weather data. It can include fire ignition and suppression as stochastic processes.	Weather and ignition inputs are generated within the software based on provided data. The user must create a spatial landscape file including information on topography and fuels (surface and canopy); national-scale datasets are available through LANDFIRE, but require user modification to represent management effects on fuels. Finer-scale local data should be used instead of LANDFIRE where available.	FSim produces raster outputs of the annual burn probability and the conditional flame-length probabilities of six flame-length classes. It also creates vector outputs of the final wildfire perimeters of the fires generated with associated attributes.	To use FSim outputs for smoke dispersion modeling in HYSPLIT, the user will need to identify specific fire locations and sizes from the burn probability and fire size outputs. This will require decisions about cutoffs in burn probability and manipulation of the spatial output data. HYSPLIT also requires a burn duration for each fire, which is not an FSim output. Therefore, the user will need to estimate these, possibly based on literature.	The FSim software is free, and it is possible to run FSim with nationally available data, but some data processing will be required to get the data into the required format. Subject matter expertise and geospatial skills will be needed to link FSim outputs to other predictive models.	Karen Short, Rocky Mountain Research Station	Finney et al. (2010) validated burn probability from historical records for fire planning units across the U.S.

Table 1. Predictive Model Summaries: Fuel and Fire Dynamics (continued)

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
The Interagency Fuel Treatment Decision Support System, Landscape Burn Probability (IFTDSS LBP)	Landscape Burn Probability (LBP), modeled by IFTDSS, quantifies the relative likelihood and intensity of a fire occurring under a fixed set of weather and fuel moisture conditions. Different than FSim—IFTDS LBP calculates burn probability and conditional flame length for a fixed set of weather conditions for a single burn period. The Large Fire Simulation Model used in many national, regional, and unit level assessments, calculates results based on variable weather inputs for fires burning multiple days throughout an entire fire season. The model is driven by FlamMap.	Inputs for wind, crown fire, initial fuel moisture, fuel moisture conditioning, simulation time, and spotting are required to run IFTDSS LBP.	Burn probability, conditional flame length, and integrated hazard are the primary outputs, all of which are rasters. The integrated hazard raster can give some information on the risk of fire for various assets such as property.	The model can accommodate data from the user such as shapefiles for study area, wind grids, and fuel loads. The interface for the model, Map Studio, comes with a plethora of publicly accessible data, especially pertinent to federal agencies.	Unlike FSim, INFTDSS LBP appears to be less known by the public but more widely used by members of the USFS. The model can be run without user-specified data or geospatial software through the Map Studio interface. The tutorials and model documentation make it relatively easy to use.	Matthew Thompson, Rocky Mountain Research Station	LBP uses the same fire spread algorithm as FlamMap MTT. This algorithm has been validated for a range of sites (Arca et al. 2007; Andrews 2009; Salis et al. 2013).

Table 1. Predictive Model Summaries: Fuel and Fire Dynamics (continued)

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
LANDIS-II Dynamic Fuel System Extension	The Dynamic Fuel System Extension classifies sites into different fuel types based on species age, conifer mortality, and post disturbance information. The Dynamic Fuel System Extension is designed to produce input for the Dynamic Fire System Extension.	The Fuel Systems Extension requires the user to select a duration in years, species fuel coefficients from field data, and a fuel type table.	Outputs include raster layers of fuel types, percent confier, and percent dead fir to be used in the Fire System Extension.	The Dynamic Fire System extension requires active sites to fuel types being assigned. Therefore, the Dynamic Fuel System extension should be run immediately before Dynamic Fire System extension.	LANDIS-II is free but can only be accessed with membership to the LANDIS-II User group. External consultants are typically necessary to generate sophisticated results given the complexity of the input data. The software can be run on a standard PC.	Brian Sturtevant, Northern Research Station	None found.
LANDIS-II Dynamic Fire System Extension	The Dynamic Fire System Extension simulates large scale and long-term fire pattern, in terms of fire occurrences, burned area, weather, fire severity and damage. Based on multiple submodels, it offers a holistic simulation of various processes of forest fire.	The Dynamic Fire System Extension requires more information for the ecoregion input file than the standard LANDIS-II run. User should specify duration/size distribution, maximum duration/size, fuel moisture code (FMC) properties, fuel type, and number of ignitions. This information should be collected in the field or prescribed. Other field data necessary include an initial weather table, a dynamic weather table, fuel type table, severity calibration factor, and a fire damage table. Many of these inputs are created by the LANDIS-II Dynamic Fuel System Extension.	The Dynamic Fire System Extension generates Fire Severity Map raster layers for each time step, summary tables by event, and summary tables by time step. Tables are .csv files.	Output from the Dynamic Fuel System Extension is a compulsory input for Dynamic Fire System Extension.	LANDIS-II is free but can only be accessed with membership to the LANDIS-II User group. External consultants are typically necessary to generate sophisticated results given the complexity of the input data. The software can be run on a standard PC.	Brian Sturtevant, Northern Research Station	Syphard et al. 2011 calibrated predicted fire frequency and fire sizes based on historical means for the southern Sierra Nevada

Table 1. Predictive Model Summaries: Fuel and Fire Dynamics (continued)

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
LANDIS-II Social Climate Related Pyrogenic Processes and Their Landscape Effects (SCRAPPLE) Extension	The SCRAPPLE extension of LANDIS-II models three different types of fires: Lightning, Human Unintentional (“Accidental”) and Prescribed Fire (“RxFire”). The three types of fires behave similarly in turns of spread and mortality, and differently in terms of ignition and suppression.	SCRAPPLE requires the user to define a duration and provide raster layers of historical accidental ignitions, historical lightning ignitions, prescribed fire ignitions, accidental suppression, lightning suppression, prescribed fire suppression, a suppressions table, dead wood table, and damage table.	SCRAPPLE creates raster layers showing the day of fires, fire intensity, and fire ignition type. It also generates a fire ignition table by time step, a summary table by event, and a summary table by time step.	SCRAPPLE is able to model both the dynamic processes of prescribed fires, lacked by the Base Harvest Extension, and the interactions between prescribed fires and other fires, lacked by the Dynamic Fires System Extension.	LANDIS-II is free but can only be accessed with membership to the LANDIS-II User group. External consultants are typically necessary to generate sophisticated results given the complexity of the input data. The software can be run on a standard PC.	https://sites.google.com/site/landismodel/extensions/scrapple	Scheller et al. (2019) validated model outputs against historical fire regimes for the Lake Tahoe Basin

Table 2. Predictive Model Summaries: Forest Dynamics and Timber Harvest

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
LANDIS-II	LANDIS-II simulates forest landscapes with consideration of ecological processes including natural succession, seed dispersal, disturbances and climate change. Core framework defines the data structure that represent forest landscape. Extensions exists as separate processes to be modeled in the landscape. LANDIS-II is a pre-programmed model designed to simulate large scale (>105 ha) landscape pattern dynamics.	LANDIS-II requires the user to provide input files for the scenario, species, and ecoregions as well as an ecoregions map to specify location, a table specifying any extensions used, and an initialization file with the input parameters for the extensions. The scenario input file is created by the user to detail a model run, including information on time steps, cell size, extensions, and a directory to the species, ecoregion, and initialization files. The species input file is a table containing the tree species of interest and is typically created with field data. The ecoregion input file is also a table with the name, code, and description of the landscape classes found in the study area. This data can be taken from publicly available datasets.	LANDIS-II generates maps for each time step with the change in land cover based on the specified disturbance or succession.	LANDIS-II is designed to work seamlessly with the LANDIS-II extensions described as separate models (biomass succession, base harvest extension, dynamic fuel system extension, dynamic fire system extension, and SCRAPPLE).	LANDIS-II is free but can only be accessed with membership to the LANDIS-II User group. External consultants are typically necessary to generate sophisticated results given the complexity of the input data. The software can be run on a standard PC.	Eric Gustafson, Northern Research Station	See validation for specific modules in this section and the previous section.
LANDIS-II Biomass Succession	The Biomass Succession Extension of LANDIS-II simulates forest growth and predicts Above Ground Biomass (AGB) annually based on growth, competition, senescence and mortality of cohorts.	In addition to the standard LANDIS-II inputs, the user should also provide a climate configuration file, mortality percentage, minimum relative biomass table, sufficient light tables, species parameter table, ecoregion parameter table, fire reduction parameter table, harvest reduction parameter tables, dynamic input data table, and initial community class. These data must be obtained through field collection.	The Biomass Succession extensions generates aboveground biomass annual net primary productivity as a raster image and a summary table showing the time step, ecoregion, number of active sites, average total above ground live biomass, average NPP, and average total litter biomass.	This extension works seamlessly with LANDIS-II and the other extensions described as separate models.	LANDIS-II is free but can only be accessed with membership to the LANDIS-II User group. External consultants are typically necessary to generate sophisticated results given the complexity of the input data. The software can be run on a standard PC.	https://sites.google.com/site/landismodel/extensions/biomass-succession	Simons-Legaard et al. (2015) did a sensitivity analysis of 9 key parameters, but no validation.

Table 2. Predictive Model Summaries: Forest Dynamics and Timber Harvest (continued)

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
LANDIS-II Base Harvest Extension	The Base Harvest Extension of LANDIS-II simulates a wide range of management prescriptions, such as prescribed burning, thinning, single-tree selection and clear-cutting. The simulation is implemented in the context of management areas (MA). Within each management area, the same prescriptions are applied for each eligible stand (group of cells) as prioritized using specific ranking algorithms, until the target proportion of the MA has been cut. In existence of multiple prescriptions, the order of implementation is determined through a stochastic process, with the chance of being implemented proportional to the total area to harvest in the prescription.	The Base Harvest Extension requires a prescriptions Input file as defined by the user with at least prescription name, stand rankings, site selection, and cohorts removed. User has the option to select further parameters. User should also supply the duration, management area, stand delineations, and harvest implementation tables.	The Base Harvest extension generates a prescription map for each time step, a summary table by event, and a summary table by time step.	This extension works seamlessly with LANDIS-II and the other extensions described as separate models.	LANDIS-II is free but can only be accessed with membership to the LANDIS-II User group. External consultants are typically necessary to generate sophisticated results given the complexity of the input data. The software can be run on a standard PC.	Eric Gustafson, Northern Research Station	None found.

Table 3. Predictive Model Summaries: Air Quality and Health Effects

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
HYSPLIT	HYSPLIT is a group of models and tools that can compute atmospheric transport and dispersion. It is commonly used to simulate the transport and dispersion of pollutants and hazardous materials, including smoke from wildfires. It uses a hybrid computational approach including a moving frame of reference for calculating advection and diffusion and a fixed three-dimensional grid to compute air pollutant concentrations. Dispersion is influenced by meteorological variables and the location, duration, and size of the release.	HYSPLIT provides the model inputs for the user to select from including release type of particulate, source location, meteorological conditions, etc.	HYSPLIT generates a concentration grid, deposition grid, and emissions file. The concentration and deposition grids are provided as an image and shapefile of contours and are subject to the time period selected by the user. The emissions file reports the emission rate (mass/hour) at three-minute intervals for the emission source location (includes spatial reference in file).	HYSPLIT outputs can be used in BenMAP to determine health impacts of air quality changes. FSim outputs can inform user input in HYSPLIT to model predicted fires.	HYSPLIT is free and available as either an online tool or a desktop client. No data processing or local capacity is required for the online version. Some data processing (i.e., identifying meteorological datasets) is required for the desktop version. No GIS skills are needed to run HYSPLIT, though some subject matter expertise is beneficial.	https://www.ready.noaa.gov/HYSPLIT.php	HYSPLIT is a component of the NOAA Smoke Forecasting System; predicted smoke extent is regularly compared with observed smoke plumes, e.g. Rolph et al. 2009

Table 3. Predictive Model Summaries: Air Quality and Health Effects (continued)

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
Community Multiscale Air Quality Modeling System (CMAQ)	CMAQ is an active open-source development project of the U.S. EPA that consists of a suite of programs for conducting air quality model simulations. CMAQ combines atmospheric science, air quality modeling, and multiprocessor computing techniques to deliver fast, technically sound estimates of ozone, particulate matter, toxic compounds and acid deposition throughout the troposphere.	CMAQ requires at least two primary inputs: meteorological information (temperature, wind, precipitation, etc.), and emission rates from sources of emissions that affect air quality. Meterological inputs are provided by supported models.	CMAQ generates estimates of quantity, location, and movemnet of air pollutants including ozone, particulates, toxics, and acid deposition. Most output files use the I/O API netCDF file format. The CMAQ user manual suggests numerous external tools for visualizing, analyzing, and processing output files.	Inputs of emission rates could come from Landis, FlamMap, and FSim. Outputs can inform BenMap.	Requires expert knowledge to run. Hosted by the EPA.	Bret Anderson, Air Resource Management	Hu et al. (2008) compared air quality effects of prescribed fires near Atlanta predicted by CMAQ with measured air quality.
Comprehensive Air Quality Model with Extensions (CAMx)	CAMx addresses air pollution issues involving inert and chemically derived compounds such as ozone, particulate matter and air toxics over a range of geographic scales and time periods. CAMx treats complex chemical interactions among directly emitted emissions from anthropogenic and natural sources, and their chemical products. It is an open-source system.	Meteorological inputs are supplied to CAMx from separate weather prediction models (specifically WRF, MM5 and RAMS are supported). Emission inputs are supplied from external pre-processing systems (e.g., SMOKE and EPS3). As a limited-area deterministic model, CAMx requires specification of initial conditions at the start of a simulation period, and boundary conditions at the edge of the modeling domain. These data can be derived using output from global chemical transport models.	CMAQ generates estimates of quantity, location, and movement of air pollutants including ozone, particulates, and air toxics. Output files use the netCDF file format and are compatible with EPA's Models-3 I/O API.	Inputs of emission rates could be informed by Landis, FlamMap, and FSim. Outputs can inform BenMap.	Requires expert knowledge to run. Publicly accessible and free to use.	Bret Anderson, Air Resource Management	Johnson et al. (2017) evaluated CAMx ozone predictions in Texas with and without fire influence by comparing with observed data.

Table 3. Predictive Model Summaries: Air Quality and Health Effects (continued)

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
IMPROVE algorithm	The IMPROVE algorithm estimates light extinction based on the concentration of major air quality components. It was developed by the EPA as the basis for a regional haze metric (the deciview haze index). The current version of the algorithm was developed by Pitchford et al. in 2007.	Concentrations of various air quality components: small ammonium sulfate, large ammonium sulfate, small ammonium nitrate, large ammonium nitrate, small organic mass, large organic mass, elemental carbon, fine soil, sea salt, coarse mass, and NO2. Relative humidity data to calculate hygroscopicity values for sulfate, nitrate, and sea salt (site-specific monthly hygroscopicity values for visibility protected areas are available from EPA where relative humidity data is unavailable). Site-specific Rayleigh scattering value (available from EPA for visibility protected areas).	Light extinction, inverse Megameters	Concentrations of air quality components can be taken from air quality model (e.g., CMAQ, CAMx) outputs.	The IMPROVE algorithm is a simple equation; no special software or expertise is required.	See Pitchford et al. 2007	Algorithm performance was evaluated by comparing predicted light scattering with measured light scattering for 21 monitoring sites (Pitchford et al. 2007).

Table 3. Predictive Model Summaries: Air Quality and Health Effects (continued)

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
BenMAP-Community Edition	BenMAP uses air quality data to calculate the change in pollutant concentrations, then relates the change to health effects using concentration-response functions. These take into account the change in air quality, the change in risk of health effects, the population exposed to the air quality change, and the baseline incidence of health effects. BenMAP also estimates the value of the health effects based on the value of a statistical life or medical costs of illness.	User must input an air quality baseline grid and change grid. User specifies spatial and temporal aspects of the grids including a table with the geographic location, metric type (e.g., 1-hour daily maximum), and metric values (string of appropriate length, e.g., 365 values for daily data). The EPA meteorological grid can be used to set the baseline; the change grid can be derived from the baseline or from results of other models such as HYSPLIT (smoke dispersion). BenMAP provides population data, health impact functions, and baseline health incidence rates inputs.	BenMAP creates maps, data tables, and bar charts with predictions of health impact results for the study area, incidence results, and valuation results. Incidence results can be exported as raw incidence, aggregated incidence, and pooled incidence. Valuation results can also be exported as raw, aggregated, or pooled. BenMAP also creates an Audit Trail Report to track the analysis inputs and selected scenarios.	The air quality change grid (required as an input) can be calculated from the output air quality component concentrations of other air quality models (CMAQ, CAMx, HYSPLIT).	BenMAP software is free and can be run with publicly available data, though some subject matter expertise is ideal. Geospatial modelling skills will aid in creating the “control” baseline dataset and linking it to the smoke dispersion model (HYSPLIT).	https://www.epa.gov/benmap	BenMAP-CE creates uncertainty distributions for both health effect incidence and economic value, as described in the user’s manual (BenMAP 2018)

Table 4. Predictive Model Summaries: Hydrology and Flooding

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
SWAT	SWAT models sediment, nutrition, and runoff processes based on topography, land use and weather, at watershed to river basin scale. It is commonly used to examine the impacts of land use change and management practices.	SWAT provides many of the model inputs for the user to choose from including soil types, watershed delineations, and weather generator data. The user should provide elevation, slope, land cover, temperature and precipitation, humidity, and wind data. All of these can be found in national public datasets.	SWAT generates tables with an annual summary by monthly average of sediment, nutrition, and runoff for the study area.	SWAT runoff estimates can be used to generate flood depth grid for input to HAZUS.	SWAT is free and can be run with different user interfaces including ArcGIS and QGIS. Some subject matter and modeling expertise is required. SWAT can be run on a standard PC. SWAT is very data intensive and requires training to use effectively.	https://swat.tamu.edu/	SWAT is widely used and has been evaluated by comparison to observed flows and sediment loading in a variety of contexts (Singh et al. 2015; Khanal and Parajuli 2013; Amatya and Jha 2011).
Spatial Tools for the Analysis of River Systems (STARS)	The STARS toolbox was developed to take advantage of the FLoWS-based landscape network and provides tools to generate and format the feature geometry, attribute data, and topological relationships of GIS datasets so that they may be used to fit spatial statistical models to streams data. The STARS tools create a new directory to store this information: an .ssn object. Once the data has been reformatted and exported as an .ssn, it can be imported and analyzed in the R environment for statistical computing and graphics.	STARS requires the same initial input data as FLoWS: streams, survey sites, and a filled DEM. Users can incorporate data to fit covariates of stream temperature including stream water origin, topology, vegetation, climate, elevation, catchment area, etc.	.ssn files to be used in SSN.	STARS was designed to work in conjunction with FLows and SSN.	ArcGIS version 10.6 2 or later with advanced license and the Spatial Analyst extension 3 required. Also requires the STARS version 2.0.7 geoprocessing toolbox for ArcGIS 4 and Python version 2.7.14 5.	Dan Isaak, Rocky Mountain Research Station	See SSN (next row).

Table 4. Predictive Model Summaries: Hydrology and Flooding (continued)

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
Spatial Stream Network (SSN)	After the user formats stream data in STARS, they can input it into SSN. SSN is an R package that allows users to calculate pair-wise distances and spatial weights based on topology, fit spatial statistical models to streams data where autocorrelation is based on three spatial relationships (Euclidean, flow-connected, and flow-unconnected), estimate relationships between variables, make predictions at unsampled locations, export spatial data for use in other software programs, and visualize the spatial data.	Input data comes directly from STARS in .ssn file form. Users can incorporate data to fit covariates of stream temperature including stream water origin, topology, vegetation, climate, elevation, catchment area, etc. The NorWeST dataset provides stream temperature recordings across the western United States as well as sample models fitting environmental covariates. For the purposes of the USFS Management conceptual models, all relevant environmental covariates should be included as well as predicted changes in variables from management decisions.	Predicted stream temperature; output formats vary depending on the user's needs, but they follow standard R options including .csv files, images (maps or other spatial representation, tables, graphs, etc.	Inputs come directly from STARS.	SSN runs through R software and is free to access.	Dan Isaak, Rocky Mountain Research Station	SSN has been used to predict temperatures in streams throughout the western U.S. and validated with observed stream temperature data (Isaak et al. 2010; Isaak et al. 2017).

Table 4. Predictive Model Summaries: Hydrology and Flooding (continued)

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
HAZUS	The HAZUS methodology was originally developed for the Federal Emergency Management Agency (FEMA) by the National Institute of Building Sciences to provide a tool for developing earthquake loss estimates. Models for similar estimates for flood damages have been developed. HAZUS is a nationally applicable standardized methodology that uses Geographic Information Systems (GIS) technology to estimate physical, economic, and social impacts of disasters including casualties. HAZUS flood models can be limited to riverine only (the model is typically used for coastal flood scenarios). The model can be applied to small or large geographic ranges.	HAZUS asks the user to define or provide a study region, which can be imported as a shapefile. User should provide a DEM and a flood hazard depth grid if possible. The user also has the option to define specific buildings or facilities that are not included in the default HAZUS maps. HAZUS provides hydrology and hydraulic methodology as a substitute for user data but it is less preferable to local data.	HAZUS predicts a wide range of outputs including flood hazard maps, damage to property (cars, facilities, infrastructure, agriculture), and number of people harmed or displaced.	Runoff estimates from SWAT can be used to construct a flood depth grid (using GIS tools) for input to HAZUS.	HAZUS is free and available to public and private users. HAZUS recommends that users have some expertise in relevant fields such as hydrology, GIS, public health, engineering, etc. HAZUS requires GIS to run.	https://www.fema.gov/hazus-software	Difficult to validate against actual flood damage because comprehensive detailed damage assessments are not always done, but Gutenson et al. (2015) compared HAZUS damage estimates with historic flood damage for two floods in Alabama. Tate et al. (2015) assessed sensitivity and uncertainty of the HAZUS flood damage component.

Table 5. Predictive Model Summaries: Economic Effects

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
IMPLAN + FEAST/Aphy	IMPLAN estimates rates of economic response (jobs, labor income, and effects on local/regional economies) from resource use and other human activities. It was initially developed within USFS and then privatized, but it still regularly used within USFS. It can estimate economic activity from a variety of sectors, including recreation, timber, and USFS expenditures. While specific methods vary, many of the calculations use "response coefficients" (provided within IMPLAN and regularly updated) to translate various activity metrics into jobs, labor income, and value added to the economy. The IMPLAN rates are combined with information on resource output/use within the FEAST/Aphy spreadsheet tool.	Recreation: need # of visits categorized by activity and visitation type, expenditure profiles for different activities and visitation types (available from National Visitor Use Monitoring), and response coefficients to translate expenditures to jobs (provided within IMPLAN). Timber: need volume of timber harvested, proportion of product that goes into specific processing sectors (can use TPO data or local data), and response coefficients to translate volumes into employment, labor income, and value-added estimates (provided within IMPLAN). USFS expenditures: budget expenditure data (salary and non-salary) for various categories, including restoration, is available internally.	For each category (recreation, timber, USFS expenditures): # of jobs (direct and indirect) and labor income (direct and indirect) supported.	Output timber harvest summary data from LANDIS-II Base Harvest Extension can be used as input for the timber component of IMPLAN.	Requires access to IMPLAN (proprietary software) and knowledge of economics to run. The USFS Economic Analysis group regularly (annually with a 2-3–year lag due to timing of IMPLAN updates) at the forest level. Individual forests interested in doing scenario analysis with IMPLAN for planning purposes often work with regional economists or Enterprise economists to do so and can get access to IMPLAN.	Henry Eichman, Economic Analysis	IMPLAN is widely used for economic impact assessments in the U.S.; accuracy of specific analyses depends on the validity of available national and regional coefficients to the study area (Berck and Hoffmann 2002).

Table 5. Predictive Model Summaries: Economic Effects (continued)

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
Benefit Transfer Toolkit	The USGS Benefit Transfer Toolkit includes a database of studies assessing the total economic value of threatened, endangered, and rare species.as well as for certain recreational activities. It provides the location, species, valuation method, economic value estimate for each included value. The total number of species and recreational activities represented are limited, and total economic value for species can include both use and non-use value, but this information can be a starting point for a benefit transfer if values for a species or activity of interest are included.	The only data required is the knowledge that a certain species or recreational activity of interest exists in the study area (or is expected to exist under the management scenario).	Economic value estimate	The presence or population of species of interest, as predicted by the species distribution models described below (MaxEnt, GJAM, and expert-based models) can be used to determine where it makes sense to estimate the value of those species. While there are gaps in predictive models for estimating changes in recreational use from landscape or species variables (see gaps section below), field data or expert knowledge about recreational activity occurring in an area can be used with the BTT to estimate associated economic activity.	The Benefit Transfer Toolkit is free and simple to use.	https://sciencebase.usgs.gov/benefit-transfer/	The validity of a benefit transfer depends on the quality of the initial study and how similar the target context is to the study context in terms of the commodity being valued and the populations affected; studies assessing the validity of benefit transfers found errors ranging from 0 to more than 100% (Rosenberger and Stanley 2006).

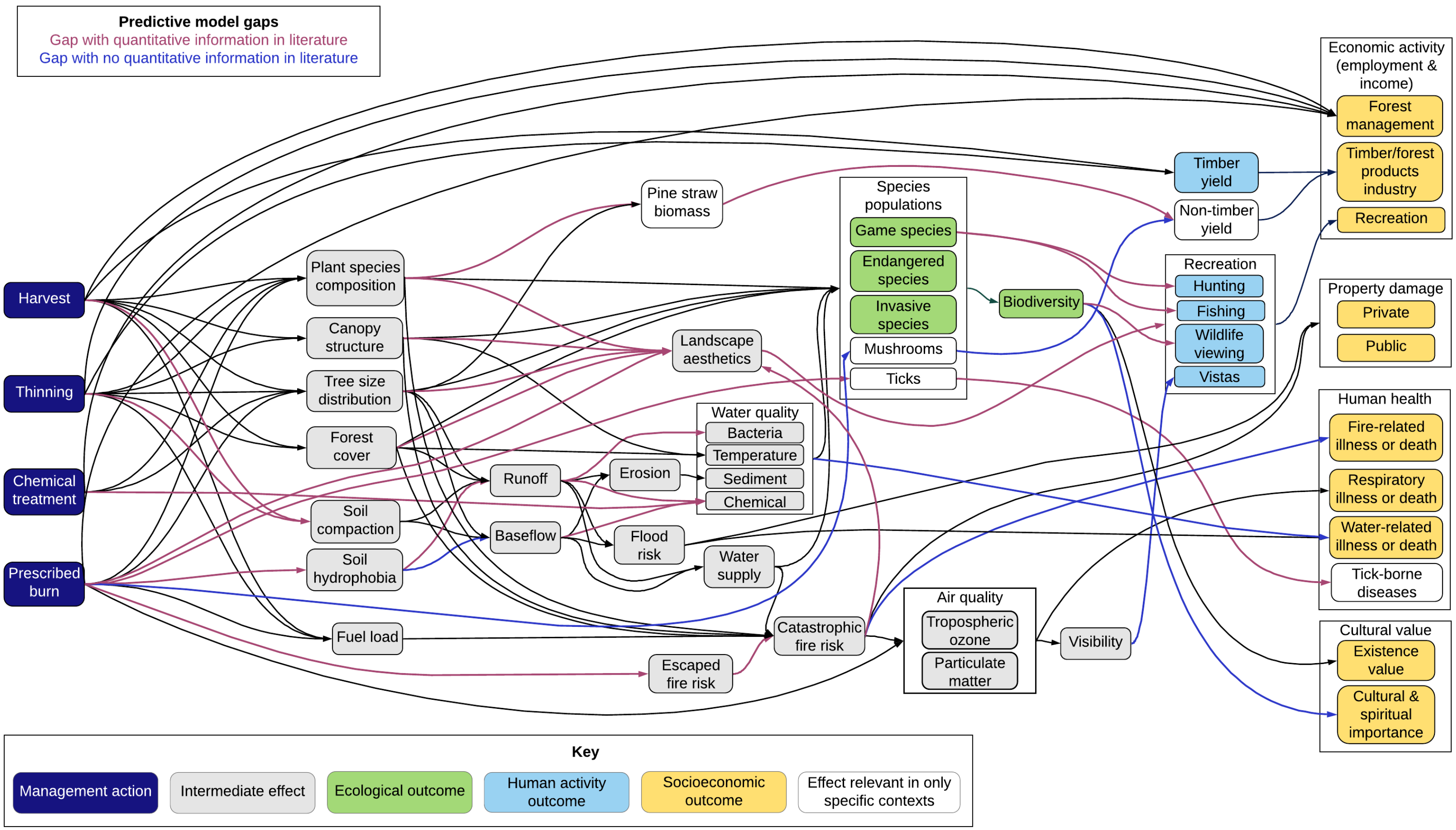
Table 6. Predictive Model Summaries: Species Distribution Models

Model name	Short description	Data requirements	Model outputs	Connectivity to other models	Capacity required	USFS contact or external resource	Evaluation
Maxent	Maxent is an open-source software that models species niches and distributions based on species occurrence data and environmental covariates. The machine-learning algorithm is based on the maximum-entropy approach, whereby the accepted distribution has the maximum entropy subject to certain constraints (the environmental covariates). If the assumptions of the model are met, the output can be interpreted as a predicted probability of presences or as predicted local abundance.	Species occurrence data: presence, absence, or pseudoabsence points represented as a shapefile. Environmental covariates: raster grid for relevant environmental variables such as precipitation, temperature, elevation, land cover, canopy structure, soil type, etc. All of the raster grids must be snapped to the same projection and encompass the same study area.	A map of predicted species abundance along with metrics for model performance.	Maxent gives information on how species react under different environmental constraints, including changes in water quality and supply, forest cover, tree size distribution, and canopy structure. Data permitting, Maxent may estimate the distribution of populations for hunting, fishing, and wildlife viewing.	Requires Maxent software (freely available) and the ability to create covariate grids and species occurrence data (GIS).	https://biodiversityinformatics.amnh.org/open_source/maxent/	Maxent has been used for a wide variety of species and geographic locations. Phillips and Dudík (2008) tested Maxent with presence data for 226 species from six regions.
GJAM	GJAM models species distribution response to environmental covariates. Unlike other SDMs, GJAM models multiple species simultaneously, and can accommodate combinations of discrete and continuous variables in a Bayesian framework. GJAM first parameterizes the response of species abundance to environmental covariates, and then predicts species abundance in a new environment. Jim Clark (NSOE and Statistical Science at Duke University) developed the model as an R package.	Species occurrence data: discrete and/or continuous (such as presence points, abundance points, basal area). Environmental covariates: raster grid for relevant environmental variables such as precipitation, temperature, elevation, land cover, canopy structure, soil type, etc.	Parameter estimates (including error terms and MCMC chains) for each predictor, along with metrics for model performance. If predicting, a map of the likelihood of species abundance.	GJAM gives information on how species react under different environmental constraints, including changes in water quality and supply, forest cover, tree size distribution, and canopy structure. Data permitting, GJAM may estimate the distribution of populations for hunting, fishing, and wildlife viewing.	GJAM is run in the R statistical environment (install.packages('gjam')).	https://cran.r-project.org/web/packages/gjam/vignettes/gjamVignette.html	The introductory paper on GJAM (Clark et al. 2016) compares GJAM predictions with tree species data and microbiome communities.

PREDICTIVE MODEL GAPS

Some of the relationships represented in the ESCM do not have relevant predictive models. Quantitative information in the literature can help to fill some, but not all of these gaps (Figure 2).

Figure 2. Predictive Model Gaps in the Ecosystem Service Conceptual Model for Fire and Timber Management on USFS Land



Relationships with Quantitative Information in the Literature

The following relationships lack predictive models, but there is some quantitative information about the relationship in the literature. In some cases, this is a predictive model that addresses some component of the relationship in the conceptual model but does not exactly match the relationship. For other relationships, there are remaining research gaps relevant to the relationship. Information in the literature may allow a researcher to quantify the relationship through rough "back of the envelope" calculations if they have relevant data and if the study area context is sufficiently similar to the research context, but these judgments would require subject matter expertise.

Forest cover, tree size distribution, canopy structure, and plant species composition → Landscape aesthetics → Recreational activities

While USFS manages for aesthetics (USFS 1995), it is difficult to consistently predict aesthetic outcomes from management actions or changes to ecosystem structure, or how aesthetics influence use of landscapes for recreation. Several research studies have developed models to predict the aesthetic quality of landscapes in certain contexts, but none has been made available for broader use. The predictive model with the greatest relevance for USFS management is the forest landscape aesthetic quality model (FLAQM), which uses artificial neural networks to predict aesthetics of forest landscapes based on tree harvesting, livestock density, virgin forest, animal grazing, and tree species richness (Jahani 2019). This model was developed in Iran based on visitor surveys in a forest; it is likely not fully applicable to the USFS context, and it only exists within a research paper. A standardized assessment of forest aesthetics implemented in Polish forests by Dudek (2018) takes into account species composition, stand age, stand structure, humidity, slope, and other landscape features, but is specific to European temperate forests. Aesthetic quality of urban-rural fringes has also been modeled based on survey responses to photos (Sahraoui et al. 2016).

Prescribed burn → Tick population → Tick-borne disease

The process by which humans are infected with tick-borne disease is complex, involving tick abundance and activity, human exposure to ticks, the rate at which ticks attach to humans, tick infection rate, and the probability of human infection from a tick bite. There has been considerable research on these components, and predictive models exist for some of them (described below), but there are currently too many unknowns to allow modeling of the entire process.

Several studies have examined the influence of fire (both prescribed burns and wildfire) on tick activity and populations. So far, this research is constrained to specific geographic areas (California, Illinois, Georgia, and Florida) (Gilliam et al. 2018; Gleim et al. 2014; MacDonald et al. 2018). Research has also focused on the risk of tick bites and disease. A 2018 study combined a tick activity model with 50,000 geolocated tick bite reports to map human exposure to ticks in the Netherlands. A follow-up study (currently in review) used the human exposure model along with tick hazard predictors to model risk of tick bites (Garcia-Marti et al. 2018; Garcia-Marti et al. in review). The research group also estimated the probability of contracting Lyme disease after a tick bite based on tick engorgement, attachment duration, and detection of bacterial DNA in ticks (Hofhuis et al. 2017).

Prescribed burn → Escaped fire risk → Catastrophic fire risk

Escaped fires are rare and caused by highly unpredictable factors (e.g., weather), as catalogued in a USFS report on escaped prescribed fires (Dether 2005); to our knowledge, there are no available predictive models to estimate this relationship. It may be sufficient to model escaped prescribed burns as a proportion of all prescribed burns, based on expert knowledge. One research paper proposed a probability-based model to determine the risk of wildfire, based on probability of fire occurrence, conditional probability of a large fire given ignition, and the unconditional probability of a large fire, but this was not designed with prescribed fire as an ignition source, and the required probabilities may not be available (unless based on expert opinion) (Preisler et al. 2004).

Wildlife populations and biodiversity → Recreational activities

While the relationships between wildlife populations and the recreational activities that depend on certain wildlife species (such as fishing, hunting, and wildlife watching) seem intuitive, related research is relatively rare. A few studies have found correlations between increased fish density and recreational fishing activity (Post et al. 2008) and number of rare bird species and birdwatching activity (Booth et al. 2011), but no models to predict recreational activity from wildlife populations were found. Some of the information in the Benefit Transfer Toolkit (USGS, more information included in the predictive model summary table) suggests that certain species are more desirable targets for fishing or hunting activity than others (participants are willing to pay more to engage in activity targeting these species), but it does not directly address the relationship between population levels and recreation. Since recreational use of USFS lands is often monitored, it may be more effective to assess management effects on recreational activity via monitoring rather than predictive modeling.

Prescribed burn → Soil hydrophobia → Runoff

The effects of prescribed burns on soil hydrophobia and runoff can be approximated by adjusting the Revised Universal Soil Loss Equation (USDA 2017), estimates soil loss as a factor of rainfall-runoff, soil erodibility, slope length, slope steepness, cover-management, and supporting practices. The model was developed by the USDA to predict long-term, average-annual erosion by water for a broad range of farming, conservation, mining, construction, and forestry uses. It is embedded in a variety of models (e.g. SWAT) and can be modified to account for the soil hydrology under different conditions. The *K factor* is a measure of the inherent erodibility of a given soil. Following a burn, the soil may become hydrophobic, especially on north-facing slopes, decreasing the infiltration capacity (Interagency Burned Area Response Team 2000). By adjusting the K factor, RUSLE may be used to determine changes in runoff and erosion. Values for K typically range from 0.10 to 0.45 (high-sand and high-clay, undisturbed soils have the lowest values whereas high-silt, disturbed soils have the highest values; Renard 1991). The severity of the burn will determine how much the K factor should be adjusted; an example of what such an approach might look like can be found in Miller et al. 2003.

Plant species composition and tree size distribution → Pine straw biomass → Non-timber forest products yield

The USDA estimates that pine stands typically yield 100-150 bales/acre (2 tons/acre) of pine straw annually, depending on conditions (USDA 2011). The amount can vary from 60 bales/acre to as much as 200 bales/acre. Tree age, species, stand density, soil fertility, management inputs, and season can affect straw yields, but quantitative information on each of these factors' effect on yields is not available.

Harvest and thinning → Soil compaction

The heavy equipment used during forest harvest and thinning operations is known to cause soil compaction, and these effects have been measured at many forest sites (Page-Dumroese et al. 2010, Shetron et al. 1988, Williamson and Neilsen 2000). However, no predictive models that specifically address the soil compaction effects of harvest and thinning were found. There are predictive models of soil compaction developed for the agricultural context; one of these, *SoilFlex*, was tested in forests in northeastern France and found to perform adequately (Goutal et al. 2013). However, the model has not been widely tested in forests and it is not known how well it would perform in USFS contexts.

Runoff → Water quality (bacteria)

There are a variety of quantitative models that can predict pathogens in watersheds, including the SWAT microbial sub-model, but most are aimed at agricultural land uses (Niazi et al. 2015). The SWAT sub-model was also developed for agricultural systems and has not been extensively tested in other types of land use (Sadeghi and Arnole 2002). One study did apply the model in areas of varying land-use type (including forest and residential), and found that it did not perform well until it was modified to better reflect bacterial growth patterns (Hwa Cho et al. 2016).

Chemical treatment, runoff, and baseflow → Water quality (chemical)

Several quantitative models are available to predict pesticide runoff from agricultural fields, including PRZM, RZWQM, and OpusCZ (Zhang and Goh 2015). SWAT also has a pesticide module that estimates pesticide transport from agricultural areas to streams; while this SWAT module has been broadly implemented in agricultural contexts, no examples of implementation in forest systems were found (Wang et al. 2019). Because SWAT pesticide transport results are very sensitive to several parameters, including some that don't have a physical meaning (so can't be estimated from experiments) and some that are spatially heterogeneous, it would be difficult to obtain meaningful results in a new context, especially a non-agricultural one (Wang et al. 2019).

Relationships without Quantitative Information in the Literature

The following relationships lack predictive models and quantitative information in the literature. This can be because the relationship is inherently difficult to measure or quantify, or because there has not been sufficient study of the relationship.

Biodiversity → Cultural and spiritual importance

Quantifying cultural and spiritual significance without directly surveying the affected communities is very difficult; no related predictive models were found, and research is community-specific and usually not applicable more broadly. Resources that describe the role of particular habitats, plants, and wildlife species in cultural and spiritual practices include Dean Moore 2007 and Forbes 2001.

Water quality → Water-related illness or death

Modeling waterborne bacterial infection is challenging for a number of reasons described by the CDC on their Current Waterborne Disease Burden Data and Gaps website (2017). In short, cases of disease cannot not be reliably ascribed to their means of contraction. Many waterborne disease can also be contracted through other means. Disease that are solely or primarily transmitted through water can be contracted by drinking water, environmental water (sprinkler systems, cleaning water, etc.), or recreational water (rivers, lakes, pools, etc.). There are also gaps in knowledge of disease incidence, because many nonfatal cases go unreported. Some predictive models related to pathogens in drinking water and subsequent waterborne disease have been developed (Jegatheesan et al. 2003, Messner et al. 2006) but these are at very small (drinking water treatment plant) or very large (national) scales and are not applicable to waterborne disease from other types of exposure, such as recreation.

Catastrophic fire risk → Fire-related illness and death

Injury and death directly caused by fire (not by fire-related respiratory effects, which are included in a different pathway) are extremely location-dependent and therefore difficult to predict. It is possible that insurance industry models examining this relationship exist, but these are proprietary and not available for general use.

Prescribed burn → Mushroom population → Non-timber yield

Morel mushrooms are valued for harvest, and evidence suggests that some species fruit prolifically after a fire, leading to increased harvest. While many studies have found high morel density following fires, a 2016 field study in Yosemite National Park suggested that many of these are overestimates due to biased, unsystematic sampling (Larson et al. 2016). The Larson et al. study developed a conceptual model of post-fire morel productivity that includes fire, soil, and plant community characteristics as well as pre-fire morel presence or absence, but did not include a quantitative model incorporating these factors. It also suggested that existing recreational harvest limits are quite conservative, and could likely be increased in post-fire years.

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