Appendix 3: Natural Range of Variation Methods and Results

Contents

1. Background

From an ecological perspective, the essence of the 2012 Planning Rule is the requirement that plan components must provide for maintenance or restoration of ecological integrity: the quality or condition of an ecosystem when its dominant ecological characteristics (for example, composition, structure, function, connectivity, and species composition and diversity) occur within the natural range of variation and can withstand and recover from most perturbations imposed by natural environmental dynamics or human influence (36 CFR 219.19; emphasis added).

As such, the 2012 Planning Rule explicitly puts the natural range of variation at the core of forest planning. As the definition suggests, it is assumed that maintaining ecosystems within the natural range of variation will provide resilience. Moreover, it is also assumed that by managing for historical ranges in stand structures by forest type on current and future landscapes, much of the habitat for native species should be recreated and maintained, and, thus, that most species and ecosystem elements should remain viable (Agee 2003). In other words, managing for the natural range of variability is at the heart of the Forest Service’s strategy for maintaining resilience and conserving biodiversity.

The natural range of variation refers to the variation of ecological characteristics and processes over scales of time and space that are appropriate for a given management application (FSH 1909.12). It represents the distribution of conditions under which ecosystems developed and gives context for evaluating the integrity of current conditions and thereby identifying important compositional, structural, and functional elements that may warrant restoration. The natural range of variation concept focuses on the variability in a subset of key ecological characteristics for use by resource managers; it represents an explicit effort to incorporate a past perspective into management and conservation decisions (Wiens et al. 2012). Understanding the causes and consequences of this variability is key to managing landscapes that sustain ecosystems and the services they offer to society.

There are a variety of methods for assessing and quantifying the natural range of variation but there is a basic tradeoff between feasibility and accurately representing the reference state (Hansen et al. 2021). In general, major forest types of the western United States have been extensively studied and there is a wealth of empirical data and theory to draw from. Given this rich dataset and the need for a relatively high level of thematic resolution for management, we are relying primarily on modeling to quantify natural range of variation for the Lolo National Forest. Specifically, we are modeling historical reference conditions using a class of landscape dynamics simulation models known as state and transition models.

State and transition models are rooted in box-and-arrow diagrams of vegetation dynamics and have several characteristics that make them well suited for modeling natural range of variation (Miller and Frid 2022). First, state and transition models are generally very intuitive, transparent, and user friendly. As such, key assumptions and results can be collaborated on, scrutinized, and assessed by a range of subject experts that may not have direct experience in landscape modeling per se. Second, state and transition models are stochastic; that is, they use probabilistic transitions to predict a *range* of possible future conditions. Consequently, simulations can be run using a Monte Carlo approach resulting in numerous possible outcomes that reflect natural variability and uncertainty, rather than a single prediction. Third, state and transition are extremely flexible allowing for increasing complexity or detail as needed. For example, they can be developed and run spatially or non-spatially and with a level of resolution that is suitable to a given application. Finally, state and transition models are well-established and widely used in the ecological research and management realm for a range of applications including rangeland management (Provencher et al. 2016), understanding invasive species dynamics (Jarnevich et al. 2019, Wilder et al. 2021), wildlife habitat suitability analysis (Haugo et al. 2015, DeMeo et al. 2018), carbon flows and climate change (Sleeter et al. 2018), and, of course, natural range of variation modeling and forest management (Haugo et al. 2015, DeMeo et al. 2018). For this analysis, we used the software ST-Sim package for SyncroSim which is ideal organizing and visualizing state and transition model inputs and outputs (Daniel et al. 2016) (http://docs.ST-Sim.net/index.html).

Notably, although natural range of variation is an important tool in assessing ecological integrity and planning, there are numerous other factors that are considered when assessing and planning for ecological integrity. Integration of natural range of variation model results with existing knowledge of ecosystems from the literature, local reports, and traditional knowledge represents a strong approach to assessing ecological integrity. Estimates of departure from natural range of variation considered without reference to the context of existing knowledge on ecosystem dynamics will be less robust than synthetic assessment of ecosystems. These considerations include maintaining conditions that contribute to long-term resilience given uncertainties in future climate and disturbances; sustaining stand structures or species compositions that provide habitat for at-risk wildlife or plant species; conserving rare structures or components; existing or anticipated human use patterns; the effects changing climate may have; and ecosystem services expected from national forest lands (such as reduction of fire hazard and production of forest products).

2. Process and Methods

For this analysis, we developed eight, non-spatial models designed to quantify the natural range of variation of the major terrestrial ecosystems on the Lolo National Forest. Here we describe the major components of model development including the vegetation stratification, climatic considerations and the development of transition pathways and probabilities for both succession and disturbance. The modeling process was conducted across both the Bitterroot National Forest and Lolo National Forest planning areas, including lands of other ownerships. This model area is referred to as the "BILO" area. Results are displayed for the Lolo National Forest planning area for this assessment.

2.1 Climate

Interannual climate variability has important regulating effects on the frequency, severity and extent of disturbance (Taylor et al. 2006, Parks et al. 2016, Abatzoglou et al. 2018). For this analysis, historic climate data was based on the Living Blended Drought Product; a recalibrated data series of June-July-August Palmer Modified Drought Index values on a 0.5 degree latitude/longitude grid, compiled by blending tree-ring reconstructions and instrumental data from the coterminous United States (Cook et al. 2009). Based on the Living Blended Drought Product data, we developed a 1,000-year time series of "wet" years (wetter than average) and "dry" years (drier than average). By using actual historic climate data but reducing it to a series of wet versus dry years, we maintain the non-random cycles of warm-dry and cool-moist climatic periods (e.g. effects of Pacific Decadal Oscillation) but allow for also some stochasticity in the interacting effects of climate and disturbance as outlined below.

To simulate the effects of climate on fire, we developed separate distributions of "multiplier" values that were associated with the set wet years and dry years. These multiplier values were applied to transition probabilities over the course of the simulation such that a multiplier value of "1" would have no effect on the transition probability, a value of 0.5 would halve the transition probability, a value of "2" would double the probability of transition, and so on. The values for the multiplier distributions were determined by assessing the relationship between acres burned and Living Blended Drought Product in the study area between 1889 and 2003 (Morgan et al. 2008) (Figure A3.1). During this time, we found that during dry years (red dots), area burned was approximately 1.7 times the overall average with a maximum of 23 times the average year in the biggest fire year (2001). In an average wet year, area burned was about 20 percent of the overall average with a maximum area burned of approximately 2 times the average year (Table A3.1).

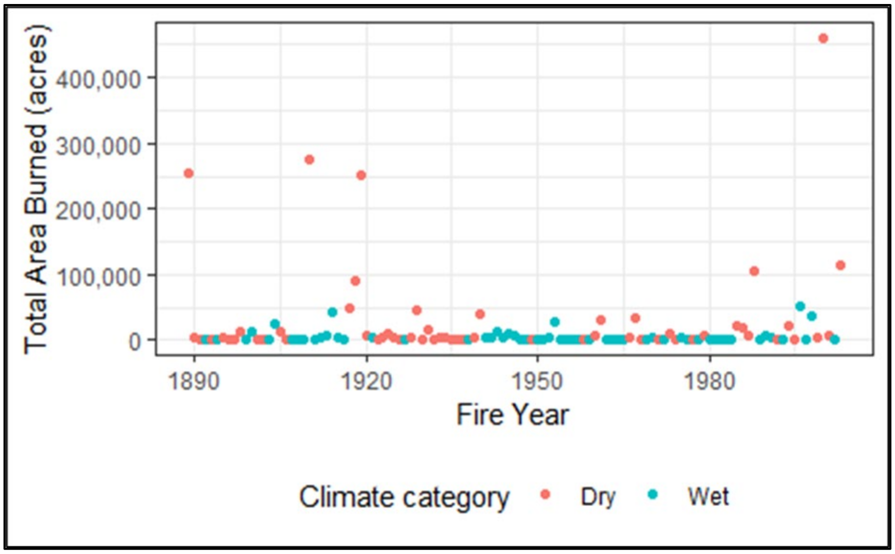

Figure A3.1—Acres burned in study area from 1890 to 2003. Red dots represent years that were drier than average and blue dots represent years that were wetter than average based on Living Blended Drought Product climate data

Table A3.1—Summary statistics of multipliers used to create variability around fire disturbance

Climate Category	Minimum Multiplier	Maximum Multiplier	Mean	Standard Deviation
Dry	0.0	23.2	1.7	4.2
Wet	0.0	2.1	0.2	0.4
All years	n/a	n/a	1	3

In the final runs, the time-series of wet versus dry years was deterministic and based on historic climate data but the *effect* of climate on disturbance was probabilistic and varied depending on the product of the base transition probability (which was based on LANDFIRE reference models as described below) and the value of a multiplier which was drawn randomly from a distribution that varied depending on whether a timestep was “wet” or “dry”. In other words, while overall mean historic fire regime information was determined based on LANDFIRE reference models, the interannual variability in area burned was linked to climate and based on data from 1890-2003. Notably, approximately 14% of the multiplier values were zero. Consequently, there was effectively no fire in these years. The purpose of adding climate-based multiplier distributions to the base-level fire probabilities was to 1) simulate the important link between climate and the probability of disturbance, and 2) model interannual variability in the area burned in a manner that resembled the observed interannual variability.

The time series of wet and dry years also affected the probability of bark beetle outbreak such that outbreaks could only occur after four consecutive dry years as described below.

2.2 Defining the Modeled Ecosystems

Broad biophysical differences, sometimes called state factors, set the context in which ecosystems operate. They include factors such as geological parent material, regional species pool, climate, and topography (Figure A3.2).

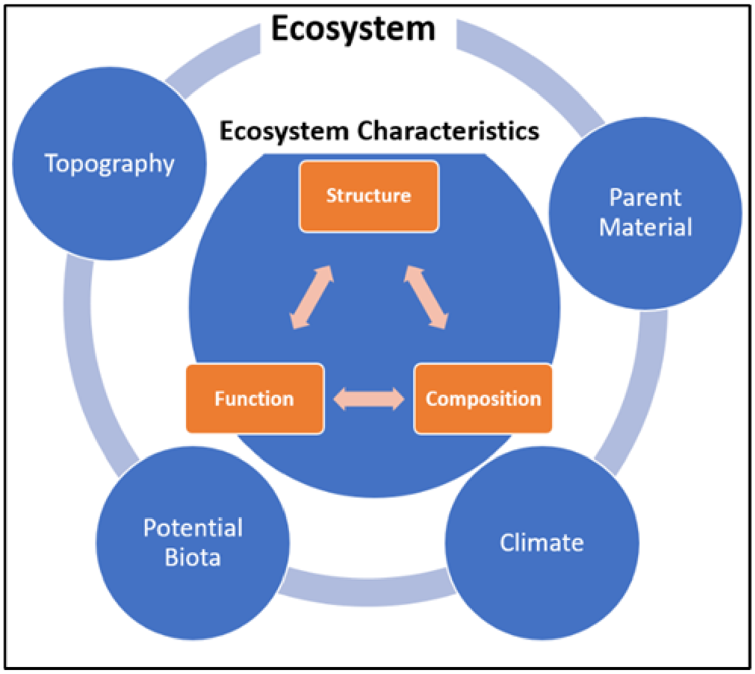

Figure A3.2—Representation of how the key components of ecosystems - structure, function, and composition - are bounded in the context of controlling state factors. Adapted from Hansen et al. (2021)

Variation in state factors across space can be simplified through classification of sites with similar characteristics into the same categorical entity. Sites within a set of state factors (e.g. different soil or vegetation types, climate domains, or other biophysical themes) can be classified at a hierarchy of thematic scales with coarse scale entities tending to include more environmental variation than fine scale entities (Oliver et al. 2022). On the Lolo National Forest, unique assemblages of plant species are classified from fine-scale plant community types called habitat types (Pfister et al. 1977), to meso-scale vegetation classes known as habitat type groups (Roberts 2022), to coarse-scale vegetation groupings known as Broad Potential Vegetation Types (Milburn et al. 2015). Each entity within each classification scale of potential vegetation types can be legitimately defined as an ecosystem – a spatially explicit, relatively homogeneous unit of the Earth that includes all interacting organisms and elements of the abiotic environment within its boundaries (36 CFR 219.19). Each ecosystem, in turn, can be defined in terms its structure, composition and function as described below.

For modeling purposes, eight ecosystems were identified representing eight groupings of habitat types. For this analysis, each ecosystem is modeled independently and there is no chance of transitioning from one ecosystem type to another. Table A3.2 displays the general environmental characteristics of each ecosystem and Figure A3.3 shows their spatial distribution. Some ecosystems, such as “Hot Arid” or “Mod Hot Dry”, are relatively rare. However, we nevertheless developed separate models for these systems because they may be more common in other national forests (and therefore will be needed in other applications) and/or they are different enough from other ecosystems to warrant a separate model.

Table A3.2—General environmental characteristics by model group

R1 Broad Potential Vegetation Type	ST-Sim Model (Ecosystem)	Major Habitat Types	Percent of Area	Mean Elevation (feet)	Total Precipitation (Inches)	Mean Temperature (Degrees Fahrenheit)
Cold	Cold Dry	PIAL-ABLA	4	7,797	46	35.1
		ABLA-PIAL/VASC				
		LALY-ABLA				
	Cold Moist	ABLA/XETE-VASC	17	6,853	45	37.2
		ABLA/LUHI-VASC				
Cool Moist	Cool Moist	ABLA/VAGL	33	5,705	42	39.5
		ABLA/LIBO-XETE				
		ABLA/CARU				
		ABLA/XETE-VAGL				
		ABLA/MEFE				
Warm Moist	Warm Moist	THPL/CLUN-CLUN	11	4,100	35	42.8
		ABGR/CLUN-CLUN				
		THPL/CLUN				
Warm Dry	Warm Mesic	ABGR/XETE	2	4,737	32	41.8
		ABGR/LIBO-XETE				
	Mod Warm Mesic	PSME/PHMA-CARU	32	4,764	26	42
		PSME/PHMA-PHMA				
		PSME/VAGL-XETE				
	Mod Hot Dry	PSME/CARU-AGSP	<1	4,615	17	42.6
		PSME/AGSP				
		PSME/SYAL-AGSP				
	Hot Arid	PIPO/AGSP	<1	3,467	14	45.8

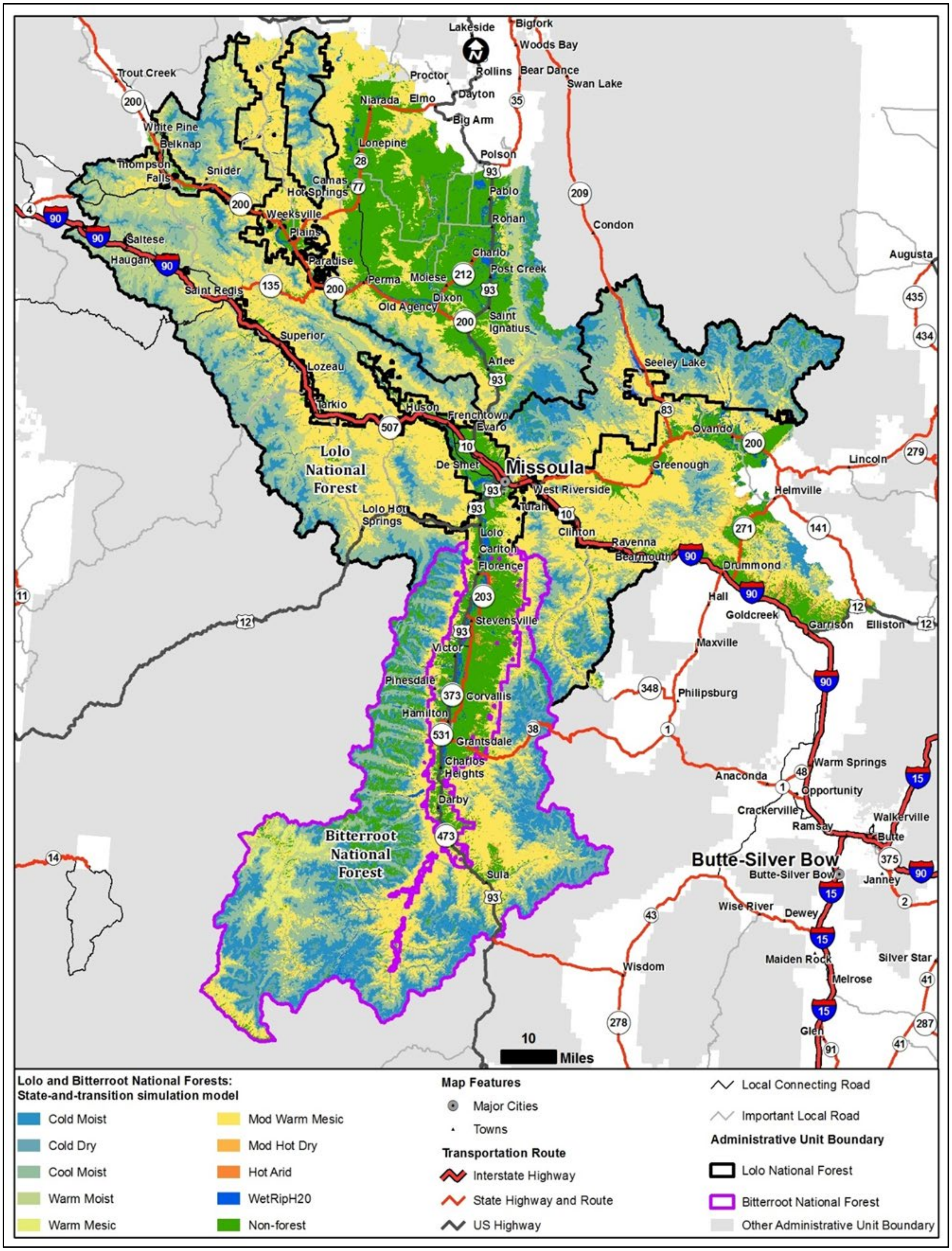

Figure A3.3—Map of modeled ecosystems across the Bitterroot and Lolo National Forests. Wetland/Riparian (WetRipH2O) and non-forest ecosystems were not modeled

2.3 Defining States within Ecosystems

Model states within each ecosystem are defined as a combination of composition and structure. The categories of stand structure and composition are defined by the Northern Region current vegetation classification and mapping systems (Barber et al. 2011, Milburn et al. 2015). Within each ecosystem, state classes were distinguished by different combinations of 1) cover type; 2) size class; 3) vertical structure; and 4) density class (Table A3.3). Not every possible combination of these four factors were included in each ecosystem. For example, no model contains the state "LPP:g2o" because this state would be extremely rare or non-existent in historic stands. Similarly, not all cover types were modeled, even if they may have existed historically or currently. This was done to keep models from getting too complex and only in cases where differences between modeled and unmodeled cover types were not linked to major differences in structure or function of the ecosystem. For example, although there are small amounts of Mixed Mesic Conifer in the Cold Dry and Cold Moist Ecosystems, the forest structure and disturbance regimes are similar enough Spruce-fir that they can be modeled together. In estimating the final natural range of variation, it may be assumed that there was some amount of these minor types on the landscape, even though they were not explicitly modeled. Table A3. 4 shows the cover types modeled in each ecosystem as well as the number of states.

Table A3.3—Composition and structure definitions of model states

Region1 Cover Type (Dominant species)	Dry Douglas Fir (DDF)
	Lodgepole Pine (LPP)
	Mixed Mesic Conifer (MMC)
	Ponderosa Pine (POP)
	Spruce-Fir (SAF)
	Whitebark-Subalpine Larch (WBP)
	Western Larch Mixed Conifer (LMC)
Size Class (Basal-Area-Weighted Mean Diameter)	H = herbs (includes grass, forb shrub)
	s = seedling/sapling (< 5")
	p = pole (>= 5" and < 10")
	m = medium (>= 10" and < 15")
	l = large (>=15" and < 20")
	v = very large (>= 20" and < 25")
	g = giant (>= 25")
Number of Canopy Layers	1 = single layer
	2 = multiple layers
Density Class (% Canopy Cover)	o = open (< 40%)
	m = moderate (>= 40% and < 60%)
	c = closed (>= 60%)

Table A3.4—Cover types (See Table A3.3 for definitions) and structural states in each ecosystem

ST-Sim Model (Ecosystem)	Cover Types	Total number of States
Cold Dry	LPP, SAF, WBP	28
Cold Moist	LPP, SAF, WBP	40
Cool Moist	LMC, LPP, MMC, SAF	94
Warm Moist	MMC	19
Warm Mesic	LMC, LPP, MMC, POP	45
Mod Warm Mesic	LMC, LPP, MMC, POP	83
Mod Hot Dry	DDF, POP	71
Hot Arid	POP	25

2.4 Growth and Succession

Growth rates and successional trajectories for state classes were derived from the Forest Vegetation Simulator Model. Forest Vegetation Simulator is a distance-independent, individual-tree forest growth model widely used in the United States to support management decision making (Crookston and Dixon 2005). Stands are the basic projection unit, but the spatial scope can be many thousands of stands. For this effort, the “stands” modeled were represented by Forest Inventory and Analysis plots. To better capture the full range of variability of stand structure and composition that may occur within ecosystem, we extended the sample domain beyond the Lolo National Forest to all Forest Inventory and Analysis plots from national forest lands that were contiguous to the Bitterroot and Lolo model area and occurred in the same ecosystems (potential vegetation types). This resulted in a total of 7,007 Forest Inventory and Analysis plots for analysis. Plots were modeled in Forest Vegetation Simulator for 300 years without disturbance to simulate natural growth. Results were output on a decadal timestep. This large-scale modeling of Forest Inventory and Analysis data was facilitated by a database Extension to Forest Vegetation Simulator (Crookston et al. 2003, Crookston and Dixon 2005) and a new translation process that allows Forest Vegetation Simulator to directly read Forest Inventory and Analysis data without the need for data conversion by the Forest Vegetation Simulator user (Shaw and Gagnon 2019).

After all plots were modeled, the final set of Forest Inventory and Analysis plots used to parameterize the model was limited based on two criteria. First, we eliminated plots where the potential vegetation type, structure or composition classifications did not succinctly nest within the modeling vegetation stratification framework. This criterion primarily eliminated plots that were in an early seral or non-forest condition of potential vegetation type. Next, we identified and dropped plots which decreased in size class over time. Because these plots had a disproportionate effect on summary growth statistics at the ecosystem-level, we used a minimum of 0.1” per decade in diameter at breast height as minimum growth rate. While slower growth rates are known to occur in high density stands or stands with very low resource availability, we found that most plots with very slow or even negative growth rates were being highly influenced by the regeneration assumptions in Forest Vegetation Simulator and the associated effects that large inputs of seedlings have on the average stand diameter. A total of 5,225 plots were used for the final analysis (Table A3.5).

Table A3.5— Number of Forest Inventory and Analysis plots in the analysis area used to simulate stand-level growth in Forest Vegetation Simulator

ST-Sim Model (ecosystem)	FIA Plots
Cold Dry	383
Cold Moist	848
Cool Moist	1,360
Hot Arid	343
Mod Hot Dry	264
Mod Warm Mesic	1,392
Warm Mesic	145
Warm Moist	490

Growth transitions in the ST-Sim model occur in one of two ways: deterministic or probabilistic pathways. Deterministic pathways represent the fate of a stand that remains in any particular state for a particular set of time without disturbance. It is assumed that without major disturbance, a stand will grow to the next largest size or density class after a certain amount of time. Probabilistic transitions provide additional successional pathways and help reflect the true variability in stand development observed in natural forests. For example, without disturbance, the state class “Cool Moist – LMC:l1m” (i.e. a large, single-story, medium-density stand with a larch mixed conifer cover type in the Cool Moist ecosystem) has some probability of transitioning into of a variety of cover or structure combinations (Table A3.6). If none of these probabilistic successional transitions occur and there is no disturbance, the stand will grow into the next size class after a certain amount of time based on the deterministic transition logic. The parameters for both deterministic and probabilistic transitions were all based on output from the Forest Vegetation Simulator model.

Table A3.6—Example of probabilistic successional pathways for a state in the Cool Moist Ecosystem. All pathways and associated probabilities were based on Forest Vegetation Simulator model outputs

ST-Sim Model (ecosystem)	State Class	To Class	Probability
Cool Moist	LMC:l1m	LMC:l2m	0.0008
Cool Moist	LMC:l1m	LMC:v1m	0.0148
Cool Moist	LMC:l1m	MMC:l1c	0.0008
Cool Moist	LMC:l1m	MMC:l1m	0.0041
Cool Moist	LMC:l1m	MMC:v1m	0.0008
Cool Moist	LMC:l1m	SAF:v1m	0.0008

Programming the deterministic transitions required designating the successional pathway (what the state transitions into) as well as the amount of time before the transition would occur. As mentioned, the default pathway for deterministic growth is an increase in size class with other structural characteristics staying the same. If that state was not available, it was assumed that density and/or vertical layering and/or presence of more shade-tolerant species increased. The average time required for a stand to grow 5 inches (i.e. grow through a size class) was calculated and used as the residence time before triggering a deterministic transition. Rather than calculate the average growth rate for each state class, we assumed that growth would vary primarily as function of broad potential vegetation type (the largest grouping of potential vegetation types – Table A3.2), size, and density. Residence time in a particular state was estimated by calculating the annual growth rate of each stand at each timestep and then averaging all growth rates for each unique Broad potential vegetation type x size x density combination (Table A3.7). By grouping state classes based on these criteria, we were able to increase the sample size for growth rates estimates as some state classes were not as common in the current inventory data. All Grass/Forb/Shrub stages were assumed to last ten years. It was assumed that stands would remain in the largest and densest state available until transition due to disturbance.

Table A3.7—Residence time (years) for a stand in a particular size, density, and potential vegetation type

Broad Potential Vegetation Type	ST-Sim Mods	Density Class	Grass, forb, shrub	Seedling sapling	Pole-sized	Medium	Large	Very large	Giant
				0-5”	5-10”	10-15”	15-20”	20-25”	>25”
Cold	Cold Dry, Cold Moist	Open	10*	33	47	75	94	95	85
		Medium	n/a	n/a	58	119	118	90	82
		Closed	n/a	n/a	n/a	99	91	86	999
Cool Moist	Cool Moist	Open	10	29	33	53	75	85	124
		Medium	n/a	17	38	81	112	105	116
		Closed	n/a	38	75	100	88	75	999
Warm Moist	Warm Moist	Open	10	19	21	28	n/a	n/a	n/a
		Medium	n/a	15	29	51	65	85	140
		Closed	n/a	n/a	45	69	87	90	999
Warm Dry	Mod Hot Dry, Hot Arid, Mod Warm Mesic, Warm Mesic	Open	10*	26	28	36	52	66	179
		Medium	n/a	15	31	64	89	101	121
		Closed	n/a	n/a	57	88	93	84	999

Residence time of 999 indicates the end of a successional pathway. In addition to the set residence time, there is also some probability of delayed regeneration which would keep a stand in a GFS for longer. *All models assume 10 years maximum age in the GFS stage except cold Dry and Hot Dry which assumes 30 and 20 years respectively.

To determine the probabilistic successional pathways and their associated probabilities, all Forest Inventory and Analysis plots were first classified into the associated ST-Sim model state classes based on their composition, structure, and potential vegetation type. At most timesteps, the stand would remain in the same state. In other words, the stand would get older, but growth was not sufficient to change size class, density class, vertical structure class or cover type. When a state did transition to another state, that pathway was implemented in the model as a successional pathway and the probability was calculated as the ratio of the number of times that a transition was observed to the total number of observations within a state.

2.5 Insect and Disease

Our approach to insect and disease modeling incorporated both background levels of disturbance, and periodic outbreaks. First, insect and disease agents were divided into three categories: root disease, defoliators, and beetles, with different probabilities, effects, and affected vegetation for each (Table A3.8 and Table A3.9). All disturbance agents may reduce stand density, but beetles tend to target large trees, while defoliators mostly impact smaller trees, and root diseases impact all sizes equally, so impacts on size class vary by disturbance agent. Disturbance probabilities were initially based on observations from annual aerial detection surveys for individual agents, but examination of results revealed that these probabilities resulted in too little insect and disease occurrence. Thus, probabilities were calibrated to create more significant levels of insect outbreak impacts that are known to occur within multidecadal dry periods.

This updated modeling approach assumed that low-level insect activity, which often interacts with disease-infested or physiologically compromised trees, is largely represented through the modeled root disease and defoliator impacts. Spatially synchronized and widespread insect outbreaks in the Northern Region have occurred in conjunction with current (2000-now) and prior (1917-1942) multidecadal dry cycles that exposure forest vegetation adverse climate conditions including frequent atmospheric precipitation dry anomalies in summer months that interact with temperature to promote soil moisture deficits and forest vulnerability (Jenne and Egan 2019, Lestina et al. 2019, Williams et al. 2020). Conversely, bark beetle outbreaks during multidecadal wet cycles, such as the pluvial period from 1980-1999, caused spatially localized and limited insect-caused damage over shorter time periods based on review of historic Northern Region aerial survey data from 1962-2022.

Research suggests that historic beetle outbreaks across past millennia were infrequent, but often caused spatially widespread mortality impacting high proportions of susceptible host in a manner comparable to present-day outbreaks, based on pollen records showing periodic significant declines in pine species that are not otherwise explained by fire or climate (Watt et al. 2022).

Root disease probabilities were largely based on Hagle (2009, 2010) and current root disease expression as quantified by Forest Inventory and Analysis data. Current Forest Inventory and Analysis data indicates that 9% of the mixed mesic conifer cover type and 10% of the spruce/fir cover type on the Bitterroot and Lolo forests are infected with mid or high levels of root disease. This level is assumed to result in an expression of effect; a change to some combination of size class, density class or cover type from what was on the site before the expression. This level is also assumed to be a “steady state”; that is, while the areas where root disease expression occurs rotate across the landscape, the overall amount in these conditions is relatively stable. Additionally, the Hagle study indicates that it takes about 15 years for root disease to have an effect on a site. By inference, to maintain a steady state at 10% mid-high infection, it must also transfer out of this state at the same rate (every 15 years; through disturbance, succession, or further degradation). Therefore the annual rate of new expression is the rate * total expression, or (1/15)*0.1 = 0.006667. This is the base probability of root disease in the model. The publication also indicates that the spruce fir cover type is only affected on the cooler and wetter sites, which represent about 69% of the cover type’s total. Therefore, the multiplier for the spruce/fir on the Cold setting was modified to 0 and the multiplier on the cool moist site was modified to 0.006667/.69 = 0.00963.

We next created cycles of outbreaks for beetles and for defoliators. For beetles, outbreaks were set to occur when there were four consecutive years of dry weather, and no previous outbreaks within the last 60 years. Outbreaks lasted 7-9 years and occurred at a rate of 1-3 outbreaks per century as suggested by dry cycle frequency documented in Williams et al. (2020) for western U.S. During these outbreaks, beetle probabilities were multiplied by 1.5-17, with the multiplier selected at random from a uniform distribution. In non-outbreak years, beetle probabilities were multiplied by 0.12. These multipliers were selected so that over many iterations of a 1000-year simulation, the beetle multiplier would average out to 1. Defoliator outbreaks occurred at a similar duration and slightly lower frequency than beetle outbreaks, with an occurrence sequence that was not based on climate. Multipliers for defoliator probabilities ranged from 1.5-15 in outbreak years and were set to 0.034 in non-outbreak years.

Table A3.8—Impacts and probabilities of root disease, defoliators, and beetles

Disturbance	Transition
Root diseases	Each susceptible state may undergo any of the following transitions:
	1. Reduce size and density
	2. Reduce density
	3. Reduce size
	4. Maintain same state but reset age
	If all these states exist in the model, root disease may cause transitions into all of these states
	If other cover types exist in the PVT, cover type shifts to a non-susceptible cover. Proportion is divided evenly between all available non-susceptible cover types.
Defoliators	Each susceptible state may have one or more of following transitions.
	First Tier:
	· Reduce density class
	· Increase size class
	· Decrease density AND increase size
	If all of the First-Tier states exist in the model, defoliators may cause transitions into all of these states. If none of these states exist, defoliators will cause a transition to a Second-Tier state.
	Second Tier:
	· Decrease density AND number of canopy layers
	· Increase size AND decrease canopy layers
	· Decrease canopy layers
	Only the first applicable transition state is used from the Second Tier, and only if none of the First-Tier states exist in the model. Proportion is divided evenly between all available destination states.
Beetles	Each susceptible state may have one or more of following transitions.
	First Tier:
	· Reduce density class
	· Reduce size class
	· Reduce density AND size class
	· Reduce size class by two
	· Reduce density class by two
	For lodgepole pine, transition options include both staying as lodgepole pine, or transitioning to mesic mixed-conifer. In the ColdDry PVT, lodgepole pine may also transition to spruce-fir cover. In ColdMoist, whitebark pine may transition to sprucefir or may stay as whitebark.
	If all the First-Tier states exist in the model, beetles may cause transitions into all of these states. If none of these states exist, beetles will cause a transition to a Second-Tier state.
	Second Tier:
	1) Reduce size, density, AND number of canopy layers.
	Proportion is divided evenly between all available destination states.

Table A3.9—Vegetation impacted by each insect and disease transition type

	Attribute	Root disease	Defoliator	Bark beetle
Size	Grass/forb/shrub	Y	N	N
	Seedling/sapling	Y	N	N
	Pole-sized	Y	Y	N
	Medium	Y	Y	Y
	Large	Y	Y	Y
	Very large	Y	Y	Y
	Giant	Y	Y	Y
Density	Open	Y	N	N
	Medium	Y	Y	Y
	Closed	Y	Y	Y
Vertical Structure	Single-story	Y	N	Y
	Multi-story	Y	Y	Y
Cover Type	Dry Douglas-fir	N	N	Y
	Larch mixed-conifer	N	N	Y
	Lodgepole pine	N	N	Y
	Mesic mixed-conifer	Y	Y	Y
	Ponderosa pine	N	N	Y
	Spruce-fir	Y	Y	N
	Whitebark pine	N	N	Y
Potential Vegetation Type	Cold Dry	N	Y	Y
	Cold Moist	N	Y	Y
	Cool Moist	Y	Y	Y
	Hot Arid	N	N	Y
	Moderately Hot Dry	Y	N	Y
	Moderately Warm Mesic	Y	Y	Y
	Warm Mesic	Y	Y	Y
	Warm Moist	Y	Y	Y

2.6 Fire

Fire parameters for the natural range of variation modeling require estimates of historical fire regime characteristics. Historical fire frequency and severity estimates drive the yearly probabilities of fire occurring and its likely severity. In addition, some idea of potential fire sizes and the cycle of large fire years will drive estimates of the multipliers of fire probabilities. Finally, “fire pathways” that are the result of historical fires of varying severities are needed to model fire’s effect on vegetation.

2.6.1 Fire Frequency and Severity

LANDFIRE fire regime attributes derived from the LANDFIRE biophysical setting reference models (https://landfire.gov/bps-models.php) were evaluated for their use in parameterizing the ST-Sim models for natural range of variation modeling. This evaluation began with “conceptually” matching LANDFIRE biophysical setting models with each St-Sim Model Group based on descriptions of biophysical setting and species composition. In addition, we spatially matched LANDFIRE biophysical setting model maps with ST-Sim Model Group maps. As a result of this analysis, we identified eight candidate biophysical setting models and the associated fire regime information that contained the necessary information to parameterize each Model Group for execution in the ST-Sim model (Table A3.10). To capture the variability within each model, we assigned a LANDFIRE biophysical setting to each cover type within each model along with the associated biophysical setting fire regime characteristics (Table A3.10).

Table A3.10—Candidate LANDFIRE biophysical setting models used parameterize fire frequency and severity of ST-Sim model

LANDFIRE Biophysical Setting Name	Mean Fire Return Interval (Years)	Percent Stand Replacing Fire	Percent Mixed Severity Fire	Percent Low Severity Fire
Dry-Mesic Spruce-Fir Forest and Woodland	138	67	33	0
Subalpine Woodland and Parkland	182	46	54	0
Mesic-Wet Spruce-Fir Forest and Woodland	180	100	0	0
Mesic Montane Mixed-Conifer Forest	79	43	57	0
Dry-Mesic Montane Mixed Conifer Forest - Grand Fir	70	32	58	0
Dry-Mesic Montane Mixed Conifer Forest - Larch	38	19	54	27
Dry-Mesic Montane Mixed Conifer Forest - Ponderosa Pine-Douglas-fir	19	13	38	49
Ponderosa Pine Woodland and Savanna	12	4	23	73

Table A3.11—Assignment of cover types within ST-Sim Models to a LANDFIRE Biophysical Setting

ST-Sim Model	Cover Types	LANDFIRE Biophysical Setting Name
Cold Dry	Subalpine Fir	Rocky Mountain Subalpine Mesic-Wet Spruce-Fir Forest and Woodland
	Lodgepole Pine	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland
	Whitebark Pine	Northern Rocky Mountain Subalpine Woodland and Parkland
Cold Moist	Subalpine Fir	Northern Rocky Mountain Subalpine Woodland and Parkland
	Lodgepole Pine	Northern Rocky Mountain Subalpine Woodland and Parkland
	Whitebark Pine	Northern Rocky Mountain Subalpine Woodland and Parkland
Cool Moist	Lodgepole Pine	Rocky Mountain Subalpine Mesic-Wet Spruce-Fir Forest and Woodland
	Mesic Mixed Conifer	Northern Rocky Mountain Mesic Montane Mixed-Conifer Forest
	Subalpine Fir	Rocky Mountain Subalpine Mesic-Wet Spruce-Fir Forest and Woodland
	Larch Mixed Conifer	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Ponderosa Pine-Douglas-fir
Warm Moist	Mesic Mixed Conifer	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Larch
Warm Mesic	Mesic Mixed Conifer	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Grand Fir
	Lodgepole Pine	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Grand Fir

ST-Sim Model	Cover Types	LANDFIRE Biophysical Setting Name
	Larch Mixed Conifer	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Larch
	Ponderosa Pine	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Ponderosa Pine-Douglas-fir
Mod Warm Mesic	Larch Mixed Conifer	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Larch
	Mesic Mixed Conifer	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Larch
	Lodgepole Pine	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Larch
	Ponderosa Pine	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Ponderosa Pine-Douglas-fir
Mod Hot Dry	Dry Douglas-fir	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Ponderosa Pine-Douglas-fir
	Ponderosa Pine	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest - Ponderosa Pine-Douglas-fir
Hot Arid	Ponderosa Pine	Northern Rocky Mountain Ponderosa Pine Woodland and Savanna

2.6.2 Fire Transition Pathways

Based on stand characteristics of density, size class, and number of stories, transition logic was assigned in the ST-Sim Model in order to describe the various fire pathways. The logic differed as a function of fire severities and stand characteristics and described below in Table A3.12.

Table A3.12—Basic logic rules for assigning post fire transition pathways

Type of Fire	Transition
Low Severity Fire	Multi-story stands go down to single story.
	Generally successional states after low severity fire will do one of the following:
	· Medium and closed density stands, reduce stand density to next lowest density
	· Increase stand size class
	· Reduce density and increase size class
	· Maintain the same density and size class
	Additionally, pole-sized open stands may be converted to a grass/shrub/forb stage
Mixed Severity Fire	Generally successional states after moderate severity fire will do one of the following:
	· Takes multi-story stands down to single story
	· May reduce density by 1 or 2 classes
	· May convert stands to grass/forb/shrub
	· May increase size class and reduce density by 1 or 2 classes
	· May convert stands to a more fire-tolerant cover type.
	· Low probability of no change
High Severity Fire	Generally successional states after high severity fire will do one of the following:
	· Stands that are medium-sized or smaller are converted to grass/forb/shrub
	· All size classes of lodgepole, whitebark, or spruce-subalpine fir convert to grass/forb/shrub

Type of Fire	Transition
	· Larger size classes in other cover types may: Convert to grass/forb/shrub (most likely), stay in the same size class, converting to open single-story, or increase in size class, converting to open single-story
	· Cover type may shift to a more fire-tolerant type

2.7 Running the Model

Following the parameterization process described below, each of the eight ecosystem models are initiated with 10,000 cells. Initial conditions are based on preliminary “spin up” runs in which each model is assumed to initially have an equal area in all model states. Each spin-up model is then run for 500 years and the resulting vegetation conditions are used as initial conditions for final runs. This is done to avoid having an equilibration period in the dataset that may affect final results. Final outputs are based on 10 iterations (Monte Carlo simulations) of 1,000 years each. This time period was selected to capture historic climate that may have affected current vegetation conditions and to model full cycles of the longest fire return intervals. The final natural range of variation is described as the mid 90 percentile of the complete dataset. In other words, the lowest and highest 5% of values were truncated from the 15,000 observations of each key ecosystem characteristic (10 iterations x 1,000 years each).

2.8 Model Review

As a final step in model development, the draft methodology and model results were shared with experts in modeling and ecology for review and recommendations. Reviewers represented a broad range of perspectives including the Lolo National Forest staff, Rocky Mountain Research Station, Forest Health and Protection, Pacific Northwest Research Station, the University of Montana, Montana State University, and Apex RMS (developers of the Synchro Sim modeling software). As a result of the review process, several adjustments were made to the final model including adding a higher potential for delayed regeneration, completing formal sensitivity analysis (see below), adding a tighter link between climate and insect disturbance, add additional alternative successional pathways, and refining root disease logic (both probabilities and transition pathways).

2.8.1 Sensitivity Runs for the Lolo Natural Range of Variation

Sensitivity analyses were run on the Lolo natural range of variation models to evaluate the importance of fine-tuning and scrutinizing specific model parameters. To better interpret the model, sensitive parameters require either a higher degree of precision or a bracketed analysis approach to show ranges of possible outcomes. This also helps with setting parameters for which there is little or no information, or if there is a large cost, such as computing time, associated with recognizing more detail of a specific parameter.

The Lolo natural range of variation analysis tested seven model parameters, described below.

- **Number of cells**. Landscapes are represented by spatially dividing the area into a grid of square cells. The modeler has the option to set this number. Fewer cells logically run faster in the model and allow for rapid development and analysis. This sensitivity analysis varied the number of cells in each model at levels of 100, 1000, 10,000 and 30,000. The results indicate that the number of cells in the simulation is not a very sensitive parameter. Admittedly, this is a bit surprising, given that intuitively, more cells should display less variability in the same way that larger landscapes exhibit less variability than a single acre or parcel of land. However, the 1,000-year simulations behind this figure create a minimum of 100,000 observations for the 100-cell run. This large number could explain some of the stability in even the run with the fewest number of cells.

- **Fire Multiplier**. Fire multipliers were used to represent more or less fire in a specific year, based on the Living Blended Drought Product drought indicator. Drier years had a higher probability of a using a large fire multiplier and wetter years a lower probability. This is used to represent the correlation between dry years and more acres of wildfire. The base multiplier was derived from recent fire history. Total acres burned on the Lolo-Bitterroot area were averaged across time and normalized to 1. Each year was then relativized to this same scaling factor to create a range of multipliers of observed conditions with an average of 1. There were two sensitivity runs; factors were scaled to 0.5 of the original and twice the original.

  Size class is a good indicator of sensitivity because more fire, particularly stand-replacing fires, should result in a younger age class distribution. Not surprisingly, the 2x fire multiplier run results in more Grass and Seedling/Sapling size and less Large and Very Large size than the base run. The inverse is true for the 0.5x multiplier run. This sensitivity run indicates that the fire multipliers are a sensitive parameter and can be adjusted in calibration runs to fine-tune model performance to expected levels. One weakness with this particular run is that the base run multipliers were calibrated to result in the same overall average amount of fire as a run that did not use the multipliers. Since the 2x and 0.5x runs modified all base probabilities by the same factor, the overall fire levels from the 2x run were approximately two times the base average, and the overall fire levels from the 0.5x run were approximately half of the base average. This result corroborates that the model is working as expected.

- **Fire Probability**. Fire probabilities are the baseline chance that a cell will burn in a given year. These are consistent through the simulation, remaining the same each year. Cumulatively, the fire probabilities across all cells will result in expected values consistent with the calibration data source (LANDFIRE) and it will be a consistent level through time. The sensitivity analysis included a run to set all probabilities at 0.5 times the base and another run to set them at 2 times the base. A 1 times base run is also presented as a point of comparison.

  The resulting median level of each size class is very similar to the Fire Multiplier sensitivity run; higher probabilities result in more fire and a correspondingly higher amount of young forest and lower amounts of old growth. One surprising outcome is that both the median levels and the range of size classes are nearly the same as the Fire Multiplier run. The Fire Multiplier run should have resulted in more extreme levels at the high and low ends of the range since it varies by time period. The Fire Probability run was expected to have a similar median level to Fire Multiplier, but a tighter range in outcome values. Therefore, while it is important to set the probability levels correctly, they do not appear to affect the range of outcome values.

- **Insect and Disease Outbreak Multiplier**. Outbreaks were indicated by a consecutive series of dry climate years. There were two outbreak multipliers recognized: one for non-outbreak years and one for outbreak years. When an outbreak was triggered, the outbreak multiplier was used to affect the proportion of vulnerable stands consistent with the observed levels of infestation and effect. For the 0.5 outbreak multiplier run, the outbreak year multiplier was modified with a 0.5 factor, and the non-outbreak year multiplier was modified with a 2x factor. For the 2x outbreak multiplier run, the outbreak multiplier was modified by a 2x factor, and the non-outbreak multiplier was affected by a 0.5x factor.

  In initial models, median and ranges of structure were essentially the same in the sensitivity runs as in the control (1x) run. Further consultation with Forest Health Protection revealed that bark beetle disturbance was less then desired. Adjustments were made and results seemed to achieve objectives, but sensitivity was not rerun for this parameter after making changes.

- **Insect and Disease Probability**. This sensitivity analysis modified the base probability for insect and disease outbreaks, which was constant through all time periods in the simulation. The 0.5 run used a 0.5 factor for all base probabilities, and the 2x run used a 2x factor for all base probabilities.

  Here, lowering the probability of insect and disease effects increases the amount of older forest, and decreasing the effect increases the amount of pole-sized forest, while lowering the amount of old forest. This effect is consistent with the modeling assumptions where larger, older trees are more susceptible to insect and disease than younger, more vigorous trees. This parameter, therefore, is sensitive to the level put into the model and was therefore reviewed by the Forest Service pathologists and entomologists for accuracy and reasonability.

- Iterations Sensitivity. A full St-SIM simulation typically involves several iterations of the same model which are then evaluated with statistical summaries for range and variability analysis. More simulations take more computing time, and it is useful to investigate the added information that can be gleaned from more iterations. Intuitively, more variability should be captured with more simulations because there are more opportunities for an extreme event to happen. This sensitivity run compared instances of 1 iteration, 5 iterations, and 30 iterations.

  The number of iterations does not affect the median and quartile range values on the resulting vegetation size classes. It is notable, however, that the 30-iteration run shows the presence of more outlier values (indicated by points above or below the box). This indicates that running more simulations allows the model to probabilistically simulate instances of abnormality. However, it is unlikely that these “extreme event” scenarios will be useful in the analysis as natural range of variation ranges are typically bound to the central 90 percent ranges, which would exclude these values. There does not appear to additional information gleaned from running the model for more than 10 iterations provides additional information.

3. Results

The tables below display the modeled natural range of variability for size class (Table A3.13), density class (Table A3.14), cover type (Table A3.15) and structure class (a combination of size and density; Table A3.16). Results are displayed for each Region 1 Broad Potential Vegetation Type as well as forestwide. At the forestwide scale, results only apply to lands with a forested potential vegetation type.

Table A3.13—St-Sim model results for the natural range of variation of size class distributions

Area	Size Class	Natural Range of Variation (Percent Area)
Cold Broad Potential Vegetation Type	Grass/Forb/Shrub	2 - 17
	Seedling/Sapling	4 - 17
	Pole	14 - 30
	Medium	29 - 47
	Large	11 - 21
	Very Large	4 - 12
Cool Moist Potential Vegetation Type	Grass/Forb/Shrub	1 - 21
	Seedling/Sapling	5 - 31
	Pole	18 - 41
	Medium	22 - 44

Area	Size Class	Natural Range of Variation (Percent Area)
	Large	6 - 14
	Very Large	4 - 11
Warm Moist Potential Vegetation Type	Grass/Forb/Shrub	1 - 17
	Seedling/Sapling	2 - 20
	Pole	8 - 26
	Medium	18 - 35
	Large	16 - 28
	Very Large	12 - 31
Warm Dry Potential Vegetation Type	Grass/Forb/Shrub	3 - 32
	Seedling/Sapling	5 - 29
	Pole	6 - 22
	Medium	10 - 30
	Large	7 - 18
	Very Large	19 - 37
Forestwide	Grass/Forb/Shrub	2 - 25
	Seedling/Sapling	5 - 25
	Pole	11 - 26
	Medium	18 - 35
	Large	10 - 19
	Very Large	13 - 26

Size classes are defined by mean basal area weighted diameter in 5" classes: <5" (Seedling/Sapling); 5-10" (Pole; 10-15" (Medium); 15-20" (Large) and >20" (Very Large). Area with <10% tree cover is considered nonforest (Grass/forb/shrub). Results are displayed for structure classes within each forested R1 Broad PVT as well as at the forestwide scale.

Table A3.14—St-Sim model results for the natural range of variation of density class distributions

Area	Density Class	Natural Range of Variation (Percent Area)
Cold Broad Potential Vegetation Type	Grass/Forb/Shrub	2 - 17
	Open	29 - 46
	Medium	33 - 51
	Closed	9 - 16
Cool Moist Broad Potential Vegetation Type	Grass/Forb/Shrub	1 - 21
	Open	19 - 45
	Medium	28 - 45
	Closed	17 - 33
Warm Moist Broad Potential Vegetation Type	Grass/Forb/Shrub	1 - 17
	Open	7 - 26
	Medium	51 - 65
	Closed	10 – 28
Warm Dry Broad Potential Vegetation Type	Grass/Forb/Shrub	3 - 32

Area	Density Class	Natural Range of Variation (Percent Area)
	Open	46 - 64
	Medium	13 - 39
	Closed	4 - 8
Forestwide	Grass/Forb/Shrub	2 - 25
	Open	35 - 51
	Medium	25 - 45
	Closed	8 - 15

Density classes are defined by three classes of tree canopy cover: <10% (Nonforest, Grass/forb/shrub); 10-40% (Open); 40-60% (Medium); and >60% (Closed). Results are displayed for structure classes within each forested R1 Broad PVT as well as at the forestwide scale.

Table A3.15—St-Sim model results for the natural range of variation of cover type distributions

Area	Covertype	Natural Range of Variation (Percent Area)
Cold Broad Potential Vegetation Type	Grass/Shrub	2 - 17
	Lodgepole	14 - 27
	Sprucr/Fir	36 - 55
	Whitebark/Subalpine larch	23 - 32
Cool Moist Broad Potential Vegetation Type Warm Moist Broad Potential Vegetation Type	Grass/Shrub	1 - 21
	Larch/Mixed conifer	18 - 31
	Lodgepole	25 - 42
	Moist Mixed conifer	10 - 20
	Spruce/Fir	14 - 23
Warm Moist PVT	Grass/Shrub	1 - 17
	Moist Mixed conifer	83 - 99
Warm Dry PVT Warm Dry Broad Potential Vegetation Type Forestwide	Grass/Shrub	3 - 32
	Dry Douglas fir	2 - 6
	Larch/Mixed conifer	4 - 6
	Lodgepole	3 - 6
	Moist Mixed conifer	7 - 13
	Ponderosa pine	49 - 72
Forestwide	Grass/Shrub	2 - 25
	Dry Douglas fir	1 - 3
	Larch/Mixed conifer	4 - 7
	Lodgepole	8 - 15
	Moist Mixed conifer	16 - 21
	Ponderosa pine	24 - 36
	Sprucr/Fir	11 - 16
	Whitebark/Subalpine larch	6 - 8

Results are displayed for cover types within each forested R1 Broad PVT as well as at the forestwide scale. Only common forest cover types are included in model.

Table A3.16—St-Sim model results for the natural range of variation of structure class distributions

Area	Structure Class	Natural Range of Variation (Percent Area)
Cold Broad Potential Vegetation Type	Grass/Forb/Shrub	2 - 17
	Seedling/Sapling Size - High Density	0 - 2
	Seedling/Sapling Size - Medium Density	0 - 1
	Seedling/Sapling Size - Open Density	3 - 15
	Pole Size - High Density	3 - 6
	Pole Size - Medium Density	6 - 16
	Pole Size - Open Density	3 - 10
	Medium Size - High Density	3 - 9
	Medium Size - Medium Density	12 - 25
	Medium Size - Open Density	9 - 19
	Large Size - High Density	0 - 1
	Large Size - Medium Density	5 - 14
	Large Size - Open Density	4 - 8
	Very Large Size - High Density	0 - 1
	Very Large Size - Medium Density	2 - 7
	Very Large Size - Open Density	2 - 4
Cool Moist Broad Potential Vegetation Type	Grass/Forb/Shrub	1 - 21
	Seedling/Sapling Size - High Density	0 - 2
	Seedling/Sapling Size - Medium Density	0 - 1
	Seedling/Sapling Size - Open Density	4 - 28
	Pole Size - High Density	9 - 19
	Pole Size - Medium Density	6 - 18
	Pole Size - Open Density	2 - 6
	Medium Size - High Density	4 - 13
	Medium Size - Medium Density	10 - 25
	Medium Size - Open Density	4 - 10
	Large Size - High Density	0 - 3
	Large Size - Medium Density	3 - 7
	Large Size - Open Density	2 - 6
	Very Large Size - High Density	0 - 0
	Very Large Size - Medium Density	1 - 6
	Very Large Size - Open Density	2 - 5
Warm Moist Broad Potential Vegetation Type	Grass/Forb/Shrub	1 - 17
	Seedling/Sapling Size - Medium Density	1 - 5
	Seedling/Sapling Size - Open Density	2 - 15
	Pole Size - High Density	2 - 8
	Pole Size - Medium Density	3 - 15
	Pole Size - Open Density	1 - 7
	Medium Size - High Density	4 - 13

Area	Structure Class	Natural Range of Variation (Percent Area)
	Medium Size - Medium Density	8 - 18
	Medium Size - Open Density	2 - 10
	Large Size - High Density	3 - 8
	Large Size - Medium Density	13 - 21
	Very Large Size - High Density	1 - 3
	Very Large Size - Medium Density	11 - 28
Warm Dry Broad Potential Vegetation Type	Grass/Forb/Shrub	3 - 32
	Seedling/Sapling Size - High Density	0 - 0
	Seedling/Sapling Size - Medium Density	0 - 1
	Seedling/Sapling Size - Open Density	5 - 28
	Pole Size - High Density	1 - 3
	Pole Size - Medium Density	2 - 10
	Pole Size - Open Density	2 - 10
	Medium Size - High Density	1 - 4
	Medium Size - Medium Density	5 - 21
	Medium Size - Open Density	2 - 7
	Large Size - High Density	0 - 1
	Large Size - Medium Density	2 - 8
	Large Size - Open Density	4 - 10
	Very Large Size - High Density	0 - 0
	Very Large Size - Medium Density	1 - 6
	Very Large Size - Open Density	17 - 32
Forestwide	Grass/Forb/Shrub	2 - 25
	Seedling/Sapling Size - High Density	0 - 1
	Seedling/Sapling Size - Medium Density	0 - 2
	Seedling/Sapling Size - Open Density	4 - 23
	Pole Size - High Density	3 - 6
	Pole Size - Medium Density	4 - 12
	Pole Size - Open Density	3 - 9
	Medium Size - High Density	3 - 7
	Medium Size - Medium Density	9 - 21
	Medium Size - Open Density	5 - 10
	Large Size - High Density	1 - 2
	Large Size - Medium Density	5 - 10
	Large Size - Open Density	3 - 7
	Very Large Size - High Density	0 - 1
	Very Large Size - Medium Density	3 - 8
	Very Large Size - Open Density	9 - 17

Structure classes are defined as the combination of size and density classes, regardless of species composition. Results are displayed for structure classes within each forested R1 Broad PVT as well as at the forestwide scale.

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