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Risk Assessment for the Southern Pine Beetle

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Keywords

damage
hazard
risk
southern pine beetle

Abstract

The southern pine beetle (SPB) causes significant damage (tree mortality) to pine forests. Although this tree mortality has characteristic temporal and spatial patterns, the precise location and timing of damage is to some extent unpredictable. Consequently, although forest managers are able to identify stands that are predisposed to SPB damage, they are unable to avoid damage entirely. Instead they must manage this uncertainty using risk assessment tools. This chapter discusses the development and utility of these tools for managing the SPB.

22.1. INTRODUCTION

The southern pine beetle (*Dendroctonus frontalis* Zimmermann) (SPB) is the most destructive pest of Southeastern U.S. pine forests. The SPB is estimated to have caused $900 million worth of direct economic damage between 1960 and 1990 (Price and others 1998) and other less tangible effects to watershed, ecological, and sociological forest functions. Southern pine beetle damage has a characteristic spatial and temporal pattern that makes risk assessment an important tool for management. Periodic outbreaks comprise large numbers of discrete infestations (contiguous patches of tree mortality) that cause localized damage to some forest areas but not others. In addition, the location and timing of SPB infestation are to some extent unpredictable. These characteristic patterns of damage ensure that some forest managers will be affected by the SPB while others may not.

The values attributed to forest products and function, the spatial and temporal patterns of SPB damage, and the unpredictability of damage form the central ideas of this chapter and key concepts involved in a discussion of SPB risk. Another major theme of this chapter is that risk assessment (the process of estimating and communicating risk) is part of a larger decisionmaking process that should allow practical and effective forest management decisions to be undertaken. The scale of the SPB problem, including the geographic range of the SPB and the number of different stakeholders it affects, suggests that estimates of risk should be readily interpretable and communicable to a wide variety of forest managers and for diverse management goals. The following section objectively defines risk and its interpretation based upon these concepts.

Estimating and managing SPB risk requires an understanding of the interaction between the SPB and measurable properties of the forest. Over many decades, foresters have reported the common association of dense pine stands and slow tree growth with SPB outbreaks. Such observations have gradually developed into a more objective, scientific study of the interaction between the SPB and the forest. This chapter reviews this scientific literature, with the aim of identifying consistent factors that indicate SPB risk. Here the primary focus is to address the following, basic questions:

1. Which silvicultural, climatic, or biotic factors lead to an increased likelihood of SPB damage?
2. Given this information, how much SPB damage is likely to occur in a particular location during a given timeframe?
3. How readily can this scientific literature be interpreted, communicated, and used for effective decisionmaking?

The interpretability and communicability of risk represents a difference between ecological research designed to investigate risk factors and the dissemination of these results to practicing forest managers. One measure of the success of SPB risk research is the extent to which scientific results are used in practice. Accordingly, the chapter concludes by assessing how results from the current scientific literature have been transformed into state-of-the-art, decisionmaking tools.

22.2. WHAT IS RISK?

Everyday definitions of risk involve two fundamental concepts: damage (or loss) and uncertainty. For example, Webster's dictionary defines the noun, "risk", as "possibility of loss or injury", and suggests several synonyms including hazard and threat. For scientific or procedural purposes, a more precise definition of the term, risk, is useful. This extra precision is important for a number of reasons:

1. It enables risk analysts and managers to effectively communicate with each other and understand how estimates of risk have been calculated, what risk estimates actually mean, and how they can be used to aid decisionmaking.
2. A clear, unambiguous definition serves as a useful paradigm for guiding the collection of data and designing analyses to assess risk.

A common and widely adopted scientific definition of risk is that it is a quantification of expected damage (or loss) defined in time and space. In a variety of risk assessment fields, the concept of risk is further defined in terms of two principal components: the probability of an adverse event occurring and the damage caused by this event. For forestry applications risk has been defined as:

$$\text{Risk} = P_a \times A_d \qquad (1)$$

where P_a is the probability of an adverse event occurring and A_d is the amount of damage caused by the event (Bredemeier and others 2000, Mott 1963). For example, the total risk from the SPB to a unit area of forest can be conceptualized as the probability of the area becoming infested and (or multiplied by) the amount of damage that is likely to occur as a result of this infestation. Despite the simplicity of this framework, it should also be noted that more work is needed in order to use it to assess risk practically. For example, both the probability of an adverse event occurring (P_a) and the damage caused by an event (A_d) need to be defined precisely in time and space dimensions. In the case above, definitions and units would need to be provided for the spatial extent of a stand (e.g., 1 ha), the temporal scale of the analysis (e.g., 1 year), and measurement of damage (number of trees killed). These definitions ensure that the results of the risk assessment are scaleable (can be applied to different temporal or spatial scales), comparable to risk estimates for different areas or observations, and therefore interpretable.

Unpredictability is clearly a key concept for defining risk and also presents one of the biggest challenges to understanding exactly what risk is. Fundamental to this issue is the differentiation of risk and uncertainty. Haimes (1998) delineates risk and uncertainty as follows:

"Risk refers to a situation in which the potential outcomes can be described in objectively known probability distributions. Risk is a measure of the probability and severity of adverse effects. The term, uncertainty, refers to a situation in which no reasonable probabilities can be assigned to the potential outcomes. Uncertainty is the inability to determine the true state of affairs of a system."

For the SPB, both the probability of an infestation occurring (P_a) and the damage caused by an infestation (A_d) are unpredictable. However, this unpredictability can be represented by objectively defined probabilities or probability distributions. This probabilistic approach conforms to an intuitive understanding of risk —although it may not be possible to predict the occurrence of an event exactly, it can be defined (summarized) well enough that it becomes useful for decisionmaking.

22.2.1. Risk Assessment

Risk assessment is the process of estimating and communicating risk. It is argued that risk estimates, or indices, are ultimately a decision support tool, and that the risk assessment process should involve an understanding of specific decisionmakers and their outstanding risk assessment questions. Equation 1 defines risk using two components that are both probabilistic (conceptually at least). Since risk assessment is primarily used in situations where future events are unpredictable, fully formulated, explicit indices of risk should use probability distributions to describe the likelihood of damage occurring. For example, one might calculate as a risk output or index a probability density function that summarizes estimates of SPB-induced tree mortality for a specified time period and spatial unit.

However, in practice this is not always technologically possible, and more implied estimates of risk might be appropriate. For example, either one of the components of equation 1 could be used as a risk estimate. In this case, the risk endpoint implies risk rather than describing it explicitly. For example, deterministic values that represent the average amount of damage or loss that might occur in the future, or categorical and relative measures of the likelihood of an event occurring (e.g., high, medium, or low risk) might also be more feasible, or appropriate, implied indices of risk. In all cases, the success of a risk index is dependant on a strong definition of what it actually means.

Risk assessments are usually required to be procedurally straightforward. For example, a forester might assess risk by measuring certain properties of a stand, enter these variables into a risk model, and obtain an estimate of risk. However, irrespective of the accuracy of the model, the utility of the risk assessment also depends on the cost and inconvenience of collecting the necessary variables. In other words, risk models intended for practical applications need to balance predictability with ease of collecting the data required by the model (Lorio 1980b).

The output of risk assessments should also address questions most relevant to a forester. For example, models that provide categorical and relative outputs of risk (high, medium, or low) provide useful information for determining which areas of the landscape are more likely to suffer damage, and therefore identify where risk reduction methods (e.g., thinning) should be prioritized. They are unable, however, to determine whether a risk reduction method is actually beneficial based on a cost/benefit analysis. Similarly, forest managers might want to rescale risk outputs according to the amount of land that they currently manage and a timeframe that is most appropriate to them. For example, one landowner might be interested in the expected losses occurring within a 50 ha parcel over a 10-year period, while another might be interested in losses for a 100 ha plot over a 20-year period. Feasibly, both questions can be addressed using the same basic pieces of information (i.e., the conceptual model outlined in equation 1), but only if this information is scaleable (appropriate spatial and temporal units are included) and easily interpretable (the meaning of risk indices are well defined).

It can be concluded that risk assessment and the development of practically useful risk models and indices is subtly different from ecological research. Nevertheless, ecological understanding of the factors that predispose forests to the SPB is essential for providing effective and reliable risk assessment models. The other essential components of the risk assessment process are:

1. Identification of outstanding and important risk questions
2. Development of data collection methods and models capable of addressing these questions
3. Communication of well-defined, easily interpretable risk outputs

Section 22.3 critically reviews the current research into which stand and site variables predispose forests to the SPB. This review focuses upon research that provides models and summaries that directly address SPB risk. Section 22.3 concludes with a summary of how versions of these models are used to provide effective SPB decision support tools.

22.3. A REVIEW OF SPB RISK ASSESSMENT

It is possible to assess SPB risk at a variety of spatial or temporal scales. For example, the focus of an assessment might be an individual tree, an individual stand, or a specific region (e.g., national forest, county). Similarly, at each of these spatial scales, risk might be reported for any given time frame (e.g., a month, a year, 50 years). It can be seen that these scales are hierarchical, such that identifying individual tree risk should allow one to calculate stand risk, which in turn could be used to calculate regional risk. In large part, the spatial and temporal scale at which risk is reported should be driven by specific, practical management questions. However, reporting the spatial and temporal dimensions of risk outputs is an important component of any assessment and allows results to be readily interpreted and rescaled for different units of time and space.

Three major trends stand out from the current risk assessment literature. The first is that most studies concentrate on the spatial scale of the risk to a stand of trees. This is probably driven by the fact that data collected for SPB risk assessment is often the result of a practical requirement to visit infested stands, and because stand level measurements are the basic building blocks of forestry. Second, current risk models usually infer a measure of the likelihood that a stand will become infested during an outbreak, given the current silvicultural and environmental condition of the stand. As such, relatively few models deal with the damage that can be expected following an infestation, yet this is clearly an important component of overall risk (see equation 1). Third, current risk models most often report relative, categorical outputs of risk; for example, high, medium, or low. Correctly interpreted, these outputs allow forest managers to identify which stands are more likely to be infested than others, but do not provide absolute estimates of damage or losses. Categorical estimates of risk are subjective—high risk from one study may not be equivalent to that of another—and are difficult to interpret for different spatial or temporal scales than used in the original study.

The following sections present a detailed and critical review of the current SPB risk assessment literature. A number of terms, including risk, hazard, and susceptibility, are commonly used throughout this literature. For the purposes of this review, they are all treated as indices of risk irrespective of the terminology, but will be discussed in terms of the three main trends outlined above and their consequences for forest management. In other words, the aim of the review is to organize and critique current risk models according to the component of risk they attempt to represent, the spatial and temporal scales for which the measurement is most relevant, and the utility of the risk outputs for risk management. This review is also limited to studies that directly attribute stand and site variables to any of these indices rather than studies that detail key ecological information about the SPB but cannot be directly used to assess risk.

22.3.1. Stand Level Risk

Infestation Probabilities

A number of researchers have developed models that attempt to determine stand and site characteristics that predispose stands to SPB damage. Although differences in methodology make it difficult to directly compare the results of these models, tree vigor (represented by measurements of basal area and radial growth), landform, and soil characteristics are key components to all these models. Disturbance of the stand (lightning, mechanical damage, or wind disturbance) is also shown to be positively associated with infestations (Daniels and others 1979, Hedden and Belenger 1985, Ku and others 1980a). Tables 22.1 and 22.2 provide a list of models (discriminant analysis and logistic regression methods respectively) and the stand variables that contribute to SPB damage. It should be noted that most researchers provide a variety of models with different complexities that explore how the predictive accuracy of the models is affected by the inclusion or exclusion of certain variables. This process is useful because in practice, certain stand variables may be unavailable or difficult to measure. As previously discussed, risk assessment involves more than finding the most predictive combination of stand variables; it must also address the practical ease with which variables can collected.

Although an understanding of the factors that predispose stands to the SPB is an important qualitative output from the risk literature, in isolation it may not lead to fully informed decisionmaking. A complete decisionmaking process requires knowledge of the correlation between stand level variables and infestation incidence. For example, in practice it is important to understand how changes in a stand variable (for example, basal area) might affect the likelihood of SPB damage. This would allow a manager to address whether risk reduction methods are worthwhile. Is the cost of a treatment or management action offset by its benefit? This information is provided by an evaluation of the predictive ability of a particular risk model. Interestingly, the SPB literature highlights a major dichotomy in this understanding. Some researchers claim up to 80 percent predictive accuracy of their models. However, others report that infestations occur in less than 5 percent of even high-hazard stands. The resolution to this apparent inconsistency lies with the methodologies used to collect the data to assess risk. Understanding the reasons for this dichotomy is important for interpreting the results from these stand-level infestation models and for developing future risk assessment methodologies.

Modeling the factors that predispose stands to SPB damage requires two essential pieces of information:

1. Stand and site measurements for infested stands
2. Site and stand characteristics of stands that did not become infested

Without both pieces of information, logical, scientific methods cannot be developed that assess the probability of infestation occurrence. A fundamental problem for SPB researchers is that forests ecosystems are extensively managed (there are lots of forest to inventory), and forestry activity (hence the potential for measurement and inventories) tends to be focused around areas that have a current SPB problem. In other words, for the SPB (and many other disturbances), there is a natural tendency to make detailed observations about forest conditions only if a problem occurs. Accordingly, three different methods for sampling (obtaining details for both infested and uninfested stands) the forest might be proposed:

1. Delineate a complete, contiguous area of forest (for example, a national forest) and build stand and infestation inventories for all stands.
2. Collect information for all infested stands and an equal number of randomly selected noninfested stands.
3. Sample a given number of stands by selecting them randomly from a larger forested area.

Each sampling method has advantages and disadvantages, and also affects the methodology required to analyze data and interpret the results. Methods 1 and 2 have both been used by SPB researchers to construct risk models, and it is the difference between these methodologies that leads to difficulties in interpreting the predictive ability of the resulting risk models.

Table 22.1—Discriminant Analysis Models for Stand Risk Rating (continued on next page)

Author (location)	Model		Notes
Kushmaul and others (1979)	DS = 2.33550 – 0.01906 (PINEBA) + 0.01484 (RAD) – 0.00829 (UNDER) – 0.00613 (SOIL) – 1.71662 (BARK).		73% accuracy for infested plots and 75% for uninfested plots
Louisiana, Mississippi, and Texas Gulf Plain	DS < –0.13514 = Infested		N = 35
			(15 infested and 20 noninfested plots)
	DS = 3.06135 – 0.018342 (PINEBA) – 0.00705 (AGE) – 0.00002 (DENSITY) – 0.00880 (SITE) – 0.04085 (TOTALBA)		Correctly classified 80%of the infested and 70% of the uninfested plot subsets
	DS < –0.12736 = Infested		
	DS = 0.93080 – 0.02004 (PINEBA) + 0.01827 (RAD)		Correctly classified 93%of the infested plot subset, 65% of the uninfested subset.
	DS < –0.12917 = Infested		
	Where:	SOIL = Surface Soil Depth	
	PINEBA = Pine Basal Area (ft^2/acre)	BARK = Bark thickness (cm)	
	TOTALBA = Total Basal Area (ft^2/acre)	DENSITY = Stand Density (stems/acre)	
	AGE = Age of Pines (years)	SITE = Site Index (base age 50)	
	RAD = average 10 year radial growth		
	UNDER = Understory %		
Ku and others (1980a, 1980b)	DS = -1.50 (TOTALBA) + 3.3 (AGE) + 64.3 (RAD) + 0.93 (HARDBA).		75% accuracy
Arkansas	DS > 100 = Low susceptibility		N_{subset} =268
	1 < DS < 100 = Medium susceptibility		
	DS < 1 = High Susceptibility		
	Where:	HARDBA = Hardwood Basal Area (ft^2/acre)	
	TOTALBA = Total Basal Area (ft^2/acre)	RAD = Average Radial Growth in cm (10yr)	
	AGE = Stand Age (years)		
Porterfield and Rowell (1980 unpublished)	DS = 1.02559 - 0.00043 (VOLUME) + 1.33776 (SAW) - 2.14726 (BARK) + 0.01878 (RAD) + 0.03205 (SLOPE) - 0.00791 (PINEBA)		79% accuracy
Texas to Virginia	DS < 0.0442 = Infested		N = 1021
			547 infested and 474 uninfested plots
			74% accuracy
			N_{subset} = 119
			(69 SPB-infested, 50 noninfested)
	Where:	RAD = 10 years radial growth (mm breast height)	
	VOLUME = Total Volume in ft^3 (> 4.6 inches DBH)	SLOPE = Ground Slope (%)	
	SAW = pines > 9.6 ft3 as proportion of VOLUME	PINEBA = Proportion of total BA in pine	
	BARK = Average Bark Thickness (nearest 0.1 inch)		

Table 22.1 (continued)—Discriminant Analysis Models for Stand Risk Rating

Author (location)	Model		Notes
Hicks and others (1980)	DS = -0.51161(BT) + -0.51526(PBA) + -0.40455(AH) + 0.17528(LAF) + 0.13538(SI) + 0.17002(ADBH) +0.12525(RGI)+ 0.18884 (TSD)+ 0.10389(SST) + 0.10514(SUBST) + 0.08937 (WR) + 0.07829 (HBA)		79% Accuracy
	Unknown DS classification		
	Where:	HBA = Hardwood basal area	
	BT = Bark Thickness (cm)	SI = Site Index (m)	
	PBA = Pine basal area (m^2/ha)	SST = Surface Soil Texture	
	RGI = Radial growth Increment (last 5 years)	TSD = Topsoil Depth	
	LAF = Landform	SUBST = Subsoil Texture	
	AH = Average height (m)	WR = Water regime	
	ADBH = Average DBH (cm)		

Method 2 has been the most commonly used sampling methodology for SPB research, probably because it requires the least sampling resources. For example, Kushmaul and others (1979) used discriminant analysis to classify whether a stand became infested based on site and stand characteristics. The resulting model was then tested on an independent subset of the data (data not used to build the model) to determine the number of times that the model correctly predicts the fate of a stand based on its characteristics (predictive ability). For this study, the models yielded prediction accuracy of 70-80 percent, suggesting that the model is very good at determining which stands are likely to become infested. Consequently, a naïve, practical interpretation of these results suggests that stands with certain characteristics are very likely to become infested by the SPB.

Closer inspection suggests this conclusion is not valid. First, the model classifies stands as either infested or noninfested—two choices. It follows that one would expect to get 50 percent of classifications correct purely by chance. A 70 percent or an 80 percent classification has a different practical interpretation if compared to a null model of 50 percent accuracy. However, the most serious interpretative problem with sampling method 2 is that the data (and model) misrepresents the ratio of infested vs. uninfested stands occurring within the forest. Even during SPB outbreaks, the landscape comprises many

Table 22.2—Logistic regression models for determining infestation probabilities of stands

Author (location)	Model	Notes
Daniels and others (1979) (unknown location)	P = 1/ (1 + e $^{-(-8.599 + 0.044 (BA) + 3.309 (PINEBA))}$)	Undisturbed non-plantation stands
	P = 1/ (1 + e $^{-(-9.998 + 0.088 (BA) + 4.801 (PINEBA))}$)	Disturbed non-plantation stands
	Where:	No goodness of fit specified
	P = Probability of infestation	
	BA = Total Stand Basal Area	
	PINEBA = Proportion of total Basal Area in Pine	
Zarnoch and others (1984) (Central Louisiana)	P = 1/(1 + e $^{[4.900 - 0.030 (AGE) - 0.004 (SIZE)]}$)	
	Where:	No goodness of fit specified
	P = Estimated probability of SPB infestation over 8 years	
	AGE = Age of Substand	
	SIZE = Size of Substand (Acres)	

more uninfested stands than infested ones, and this affects the interpretation of the results. Interpreted correctly, these results suggest that if infested and uninfested stands are pre-selected from the landscape in equal numbers, the predictive accuracy of the model is 70-80 percent. This interpretation (which is correct, given the data and the analysis) does not actually address a practically useful risk assessment question. A more appropriate question, and one that can be used to make effective decisions, should directly address the probability that a stand with given attributes becomes infested in a given time period.

Other researchers have identified and addressed the problem of uneven sampling with updated analyses. For example, Hicks and others (1980) used a discriminant analysis and estimates of the sampling bias between infested and uninfested stands to determine actual infestation probabilities for stands with different attributes. In addition, the logistic regression methodology reported by Daniels and others (1979) and Reed and others (1982) uses a methodology designed to overcome these sampling problems. However, although analyses can be modified to account for unrepresentative samples, outputs will always be sensitive to the relative sampling frequency of infested to uninfested stands. The methodology of Mason and Bryant (1984) provides the most obvious solution to this problem by delineating entire portions of the landscape and collecting data for all stands—sampling methodology 3. Although not without its own problems (for example, the expense of data collection and determining an appropriate spatial scale for a study), the advantage of this method is that it encourages regular, ongoing inventories of the forest useful for assessing risk to any forest disturbance agent. In the near future, remote sensing may provide more efficient and detailed forest measurements and help overcome some of these problems and solve a fundamental problem for SPB risk assessment.

Table 22.3 shows infestation probabilities calculated by a number of researchers. In summary, these rates are between 0.01 and 5 percent even for high-risk stands. For example, Hicks and others (1980), using data from East Texas between 1975 and 1977, estimate infestation probabilities less than 0.01 (1 percent) even for stands with high basal areas (>27 m^2/ha). Daniels and others (1979) report slightly higher infestation rates during an outbreak in 1975 (undisclosed location), but for stands with a basal area between 20 and 35 m^2/ha still only estimate infestation probabilities of between 0.01 and 0.02 (1-2 percent). Reed and others (1982), estimate year by year infestation probabilities for East Texas ranging from 0.0043 to 0.0479 (0.4-4.8 percent) between 1966 and 1976 (note that parts of East Texas were under permanent outbreak conditions during this period). These estimates are based on methodologies that account for biases in sampling, and suggest that even during outbreak years the probability that any single stand will become infested is relatively low, even if the stand has attributes that predispose it to an infestation. The estimates in Table 22.3 are also scaleable in time and space. In other words, they can be used to estimate, for a typical outbreak year, the total risk for a collection (ownership parcel) of any number of stands. If outbreak frequency data are included, then they can be used to estimate the likelihood of an infestation occurring for any spatial extent and for any time period (for example, the harvest cycle of a stand—see section 22.3.2). It should also be noted that although low infestation probabilities may reduce the perceived problems (risk) caused by the SPB, when these numbers are rescaled for entire forests comprising many stands and extended time scales, these probabilities become much more significant.

In addition to providing practical risk information, it is argued that the magnitude of the probabilities in Table 22.3 conforms to current knowledge of the SPB. It is generally believed that the SPB most readily attack and infest stressed and weakened trees. This stress might be caused by a number of factors; for example drought, mechanical damage (Hedden and Belenger 1985), lightning strikes (Coulson and others 1999b, Flamm and others 1993), or flooding. In addition, it is clear that these potential hosts will only become infested if they can be successfully located by beetles (Paine and others 1984). Finally, any weakened and successfully attacked tree must be close to other potential hosts (others subject to stress) if a multi-tree infestation is to develop. So, ecologically, the occurrence of infestations may involve the co-occurrence of a number of fairly rare events. Mathematically low probability events multiply to produce even lower probability events, facts that may be important for assessing the predictive success of these models. It is therefore probably not surprising that the predictive accuracy of these models is

Table 22.3—Summary of stand-level infestation probabilities during outbreaks

Author	Location, Year	Infestation Frequency	Units	Basal Area or Risk Range
Lorio and others (1982)	Kisatchie National Forest, Louisiana	13.4	Infestations per 1000 ha	High risk
		6.8		Medium risk
		3.2		Low risk
	East Texas, 1973-1978	9.9	Infestations per 1000 ha	Very High risk
		5.8		High risk
		3.9		Moderate risk
		2.7		Low risk
		1.8		Very Low risk
Hicks and others (1980)	East Texas, 1975	0.002	Infested area/Total Host Area	All host types
	1976	0.004		All host types
	1977	0.002		All host types
	All Years by BA	0.000	Probability of infestation per ha	0.0 -9.2 (m^2/ha)
		0.000		9.3-18.4 (m^2/ha)
		0.001		18.5-27.5 (m^2/ha)
		0.001		>27.5 (m^2/ha)
Daniels and others (1979)	Unknown, 1975	0.008	Probability of infestation (Undisturbed stands)	11.48 (m^2/ha)
		0.014		22.96(m^2/ha)
		0.023		34.4 (m^2/ha)
		0.037		45.93 (m^2/ha)
		0.015	Probability of infestation (Disturbed stands)	11.48 (m^2/ha)
		0.048		22.96 (m^2/ha)
		0.131		34.4 (m^2/ha)
		0.313		45.93 (m^2/ha)

low. The resolution of forest data is driven by the practical difficulties of measuring extensive forest ecosystems—it is difficult to account for every tree in the forest. In addition, the small size and cryptic behavior of the beetle make it difficult to measure, yet its presence or absence is undoubtedly the most important factor that contributes to an infestation occurring (Paine and others 1984). Arguably, models based on aggregate, stand-level data should not be expected to be highly predictive. And from a risk assessment perspective, researchers should be reassured that even small amounts of extra information (predictive accuracy) can contribute to effective decisionmaking if it is objective, logically sound, and easily interpretable.

Infestation Growth Risk Models

Assessing the probability that a stand will experience an infestation is one component of stand-level risk. The expected amount of damage caused by an infestation completes a full assessment. The ultimate size of an infestation is driven by the potential for spot growth, which in turn may be driven by stand, site, and climatic variables similar to those that drive the initiation of infestations. But as Daniels and others (1979) point out, causal relationships important in the initiation of outbreaks (infestations) may be different from those involved in the subsequent spread of outbreaks (infestations). However, like infestation dynamics, the growth and ultimate size of infestations are to some extent unpredictable. The goal of spot growth models, especially for risk assessment, is to understand the relative importance of various site factors to spot growth and to estimate the losses likely to accrue in a stand that has become infested.

In contrast to assessments of stand infestation, there have been fewer studies on the growth or sizes of infestations. This is puzzling, since the data required to model infestation growth should comprise mostly information (excepting the role of beetle immigration and emigration) collected solely within infestations rather than for the entire forest area. It could also be argued that infestation growth and tree mortality are ultimately responsible for economic or other losses. In East Texas, the working definition of an infestation is 10 trees, but some infestations may grow to become three or four orders of magnitude larger. Understanding the factors that drive infestation growth determines overall stand damage. This level of understanding is more important for some risk assessment questions than for others. For example, over regional scales, a large number of infestations may occur. In such cases, the variability of within-stand damage may average out such that average infestation size becomes a meaningful concept. In contrast, for small private foresters who have incurred a single infestation, there may be considerable motivation to understand the amount of damage that might occur should a stand become infested.

Hedden and Billings (1979) used data collected over 3 years in East Texas to develop a model that was highly predictive in assessing the fate of infestations (Table 22.4). The model uses the number of active trees at first visit to determine the probability that an infestation will contain fewer than 20 active trees after 30 days. They also developed a model to estimate the number of trees killed per day as a function of the initial number of infested trees at the first visit, total basal area, and the total number of infestations detected for that year (Table 22.4). From a sample size of 62 spots, this equation gave an R^2 value of 77 percent. The model suggests that the total number of infestations in the landscape has a large effect on infestation growth. All other things being equal, spots showed different expansion rates for different years, with three times as many trees killed per brood during a severe outbreak year than during the collapse of an outbreak. Models without this variable failed to account for differences in the aggressiveness of spot growth for different years.

One potential criticism of this study lies in the use of initial infestation size (number of trees killed at first visit) to predict spot growth. It could be argued that if an infestation has grown large relatively quickly, then by definition it is situated in a stand suitable for spot growth and more likely to continue growing large. The interpretation provided by the authors is that the initial size of the infestation is important because it reflects the size of the resident beetle population available to sustain spot growth without dependency on immigration from surrounding infestations. It should also be noted that this difficulty arises largely as a result of the time lag between the initiation of an infestation and spot detection through changes in the color of foliage (Billings and Kibbe 1978)—another characteristic of the system that contributes to difficulties studying SPB.

Reed and others (1981) used the same data as Hedden and Billings (1979) to develop a new model (Table 22.4) that explained 77 percent of the variability of spot growth. Extending the work of Hedden and Billings (1979), they coupled this with a model that estimates the probability of an infestation becoming inactive after 30 days. These two equations can be used to simulate and predict ultimate spot size. At the beginning of the simulation, the growth equation can be used to predict the size of the spot after 30 days. The second equation can then be used to determine if, after this time period, the spot is predicted to remain active. To simulate an infestation over any period, the procedure is repeated for as long as the spot remains active.

Schowalter and Turchin (1993) addressed some of the problems of the delay between infestation initiation and measurements of spot growth by introducing beetles to stands to control for the timing of infestation initiation and initial beetle population size. Their main conclusion is that the pine basal area of the stand significantly influenced the growth of the infestations. More specifically, they found that tree mortality was significantly related to the average nearest pine distances of the stand, and the number of trees killed in each stand was highly variable. In all cases, introduced beetles attacked trees in the stand, but sometimes these attacks were unsuccessful and did not lead to infestation growth.

In addition to simple statistical models, mechanistic population models have been developed that explore the interaction between stand characteristics and infestation growth. For example, the Arkansas Spot Dynamics Model (Stephen and Lih 1985) takes basic information about the location, silvicultural characteristics of the stand, and the conditions of a current infestation (counts of infested trees) to project average growth of the infestation. Validation of the model using data from 70 infestations suggested that predictions after 90 days are subject to a 13.3 percent error. Currently, the model is in the process of being validated

Table 22.4—Summary of simple spot growth models

Author	Model
Hedden and Billings (1979)	Probability that an infestation will contain < 20 trees after 30 days =
	$1 / (1+\exp(-11.13 +3.53 \log_e (AT))$
	Trees killed per day =
	$-1.78627 + 0.02475(IAT) + 0.02765(TBA) + 0.14229(POP)$
	Where:
	IAT = Number of trees under attack at first visit
	TBA = Total Basal Area in m^2/ha and the total number of infestations detected for that year
	POP = Total number of surrounding infestations in the landscape
Reed and others (1981)	Probability of spot becoming inactive (next 30 days) =
	$1 / (1 + \exp(-1.04 + 0.06AT))$
	Natural logarithm of trees killed per day =
	$TK/D = 3.435 + 0.965 \log_e (AT) – 2.847 (\log_e DBH) – 22.137 (TBA/DBH^2) + 0.0736 (TBA) + 0.558 (POP)$
	Where:
	TK/D = Predicted natural logarithm of trees killed per day
	AT = Natural logarithm of the number of attacked trees at the start of the simulation period
	DBH = The mean DBH of the stand (cm) at the start of the year
	TBA = Total basal area of the stand (m^2/ha) at the start of the year
	POP = Number of spots per 405 ha (1,000 ac) of host type for the entire region during the year being examined
	AT = Number of affected treed at the beginning of a 30-day period.

using a much larger data set and further developed to allow it to be easily distributed to forestry professionals.

Another SPB spot growth model, TAMBEETLE, has been developed and described by Coulson and others (1989). This model differs from the Arkansas model in that it is a spatially explicit, stochastic model of population dynamics. Conceptually, the model tracks beetle populations within each tree using temperature-driven growth, fecundity, and survival rates, and simulates the emergence and reemergence of the within-tree beetles, and using this information evaluates the probability that attacking beetles will be numerous enough to overcome the defenses of neighboring trees. Note that this process is conceptually very similar to the one suggested by Reed and others (1981), except that it accounts for much more biological detail (especially the relationship between temperature and population processes), incorporates known mechanistic submodels, and runs on a time-step of 1 day instead of 30 days. Currently, the major problem with TAMBEETLE is that there are no published reports that detail the accuracy of the model.

22.3.2. Regional Scale Risk Assessment

The previous sections reviewed models that could be used to analyze risk at the scale of individual stands. In most of these studies, data were obtained for a single outbreak and for a particular region where the outbreak occurred. Southern pine beetle outbreaks can be conceptualized as having a frequency component (how often outbreaks occur within a region) and a severity component (how many

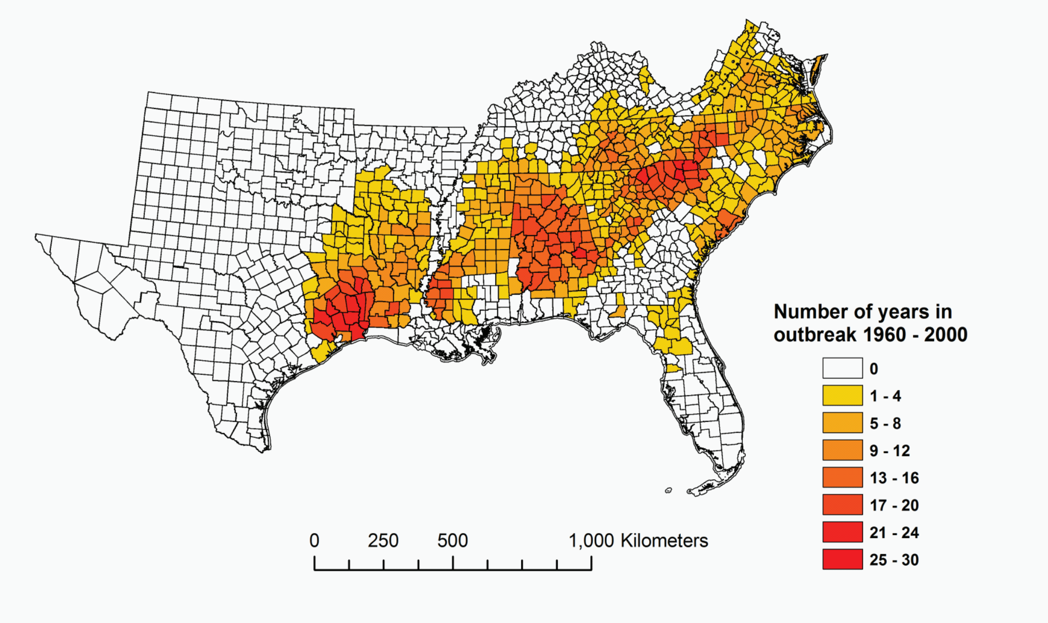

Figure 22.1—Frequency of SPB outbreaks by county between 1960 and 2000.

stands were infested as a result of that outbreak). So if strictly interpreted, because they are likely to be driven by the severity of that outbreak, infestation probabilities (and probably to some extent spot growth—see section above) are specific to a particular outbreak in a particular region. If all SPB outbreaks had the same frequency and severity, regional-scale risk would not be important. But empirical evidence suggests that this is not the case. Figure 22.1 shows the frequency of outbreaks across the range of the SPB, and it is possible that the severity of outbreaks also varies considerably across the range of the SPB. These patterns of outbreaks may be driven by factors such as climate, host availability (including the number of high-risk stands), and the structure (e.g., fragmentation) of the forested landscape.

The factors that contribute to regional SPB risk have added importance because of large-scale, human-induced changes in both climate and the state of the forest. For example, climate change may affect the range of both the SPB and its hosts, thus exposing new forest stakeholders to SPB risk. In addition, the forest is becoming more fragmented. This fragmentation concerns the physical juxtaposition of forest patches but also parcels of ownership and permeation by humans (Riiters and Wickham 2003). Physical fragmentation may directly affect SPB population dynamics, the initiation and growth of infestations, and ultimately the pattern of SPB damage, while ownership fragmentation may also be significant because it has the potential to affect an individual's interpretation of damage. For example, consider how a 100-tree mortality event might affect an individual who owns 1,000 trees vs. an individual owning 10,000. In the first case, 10 percent of a forest manager's trees (potential income) are lost, whereas in the second case only 1 percent are lost. It follows that the interaction between the pattern of SPB damage—including and especially the unpredictability of mortality—and pattern of forest ownership is an important factor for SPB risk research.

Regional-scale risk assessment requires an understanding of how climate, forest, and other relevant factors affect the larger scale spatial and temporal patterns of SPB damage. For example, quantifying the effects of regional climate and vegetation patterns on the severity and frequency of SPB outbreaks would allow extrapolation of stand-level infestation probabilities for any region of the SPB range and may also be important for assessing risk in the light of regional changes in forest structure and composition. Similarly, an understanding of the contagion of infestations would allow stand-level infestation probabilities to be estimated throughout the course of an outbreak, based on the location of a focus stand relative to existing infestations.

Most regional risk studies have focused on the effects of climate change. For example, Gumpertz and others (2000) use a logistic regression analysis to investigate the frequency of infestations in North Carolina, South Carolina, and Georgia. A number of regional-scale forest, physiographic, and climatic variables were used in the model, including estimates for the volume of timber grown in the county (pole timber and sawtimber); the proportion of habitat classified as xeric, mesic, or hydric; a number of average climatic variables for the county; the amount of land in one of five ownership classes; and three locational parameters: mean elevation, latitude, and longitude. The model accounts for and found significant spatial and temporal autocorrelation effects, suggesting that the locations of outbreaks in the previous year were good predictors of where outbreaks were likely to occur in the next year. Because of the large number of explanatory variables used in the analysis, the coefficients of the model are probably unable to provide conclusive information about which of these is most important. However, validation of the model based on 5 years of new data successfully predicted the occurrence of outbreaks and non-outbreaks 64 percent and 82 percent of the time, respectively. Furthermore, the authors argue that many of the independent variables do have some ecological relevance. For example, the amount of sawtimber in a county was considered a more useful explanatory variable than the amount of pole timber because the SPB preferentially attacks larger, more mature trees.

Gan (2004) performed regional-based risk assessment that explores the influence of selected county-level variables on total SPB damage. A panel data approach was used to model the proportion of timber killed in each county of the Southern United States over a 23-year period. Since the main focus of the work was to investigate the effects of climate change on beetle distribution and SPB risk, all but one of the independent variables used were related to current or lagged weather measurements. The model provided a good fit to the data (an R^2 of 97.5 percent), and suggests that both current and lagged weather variables are important factors that contribute to SPB damage. The author concludes that SPB risk might be increased by an average of 2.5 – 5 times for a range of predicted climate change scenarios.

22.3.3. Risk Models in Practice

One measure of the success of risk models is the extent to which they are actually used to aid practical decisionmaking. This criterion is not absolute (conceivably, poor models might prove useful for extended periods before their problems are realized). However, risk assessment is a practical process, and as many authors have noted (Kushmaul and others 1979), for a model to be practically useful, it must attain a balance between predictive ability and the amount of effort required to obtain the inputs (information) necessary to produce outputs. A review of current, procedurally used models (and who uses them) may indicate appropriate levels of detail relevant for different user groups, and identify characteristics that lead to utility.

One of the most common, practical uses of stand risk models is to help allocate Federal funds in cost-share programs that offer financial rewards to foresters who engage in good management practices. For example, in East Texas, thinning operations qualify for cost sharing if (among other factors) landowners own between 10 and 5,000 acres and if stands have greater than 70 percent loblolly, shortleaf, or slash pines, and two risk models are also used to determine qualification for cost-share programs. The first is a Texas Forest Service-defined grid (approximately 8.5 x 8.5 km cells) covering East Texas that rates geographically driven SPB risk (TFS uses the term Hazard) as Very Low, Low, Moderate, High, or Extreme (see Figure 22.2). Billings and others (1985) describe the methodology used to develop these grid block ratings, which are periodically updated to reflect changes in the forest landscape. A stand must be located in a Moderate, High, or Extreme Hazard stand in order to qualify for cost-share. The second model is site-specific and based on basal area and landform. If these conditions are met and the stand is reduced to no more than 80 square feet per acre (approximately 18.5 m^2/ha), then owners can claim up to $75 per acre for precommercial thinning or $50 per acre for pulpwood first thinning to offset the costs of the operation (Texas Forest Service document TFS 3/06/5000 should be consulted for more details).

Similar cost-share programs are administered by states across the range of the SPB. The aim is to provide incentives to individuals to reduce hazard across broad landscapes. The two-step evaluation process used by the Texas Forest Service suggests that risk is conceptualized as a property of both the local area that a stand is situated in, based on analysis of the forest landscape and past infestation history, and the potential for damage based on measured

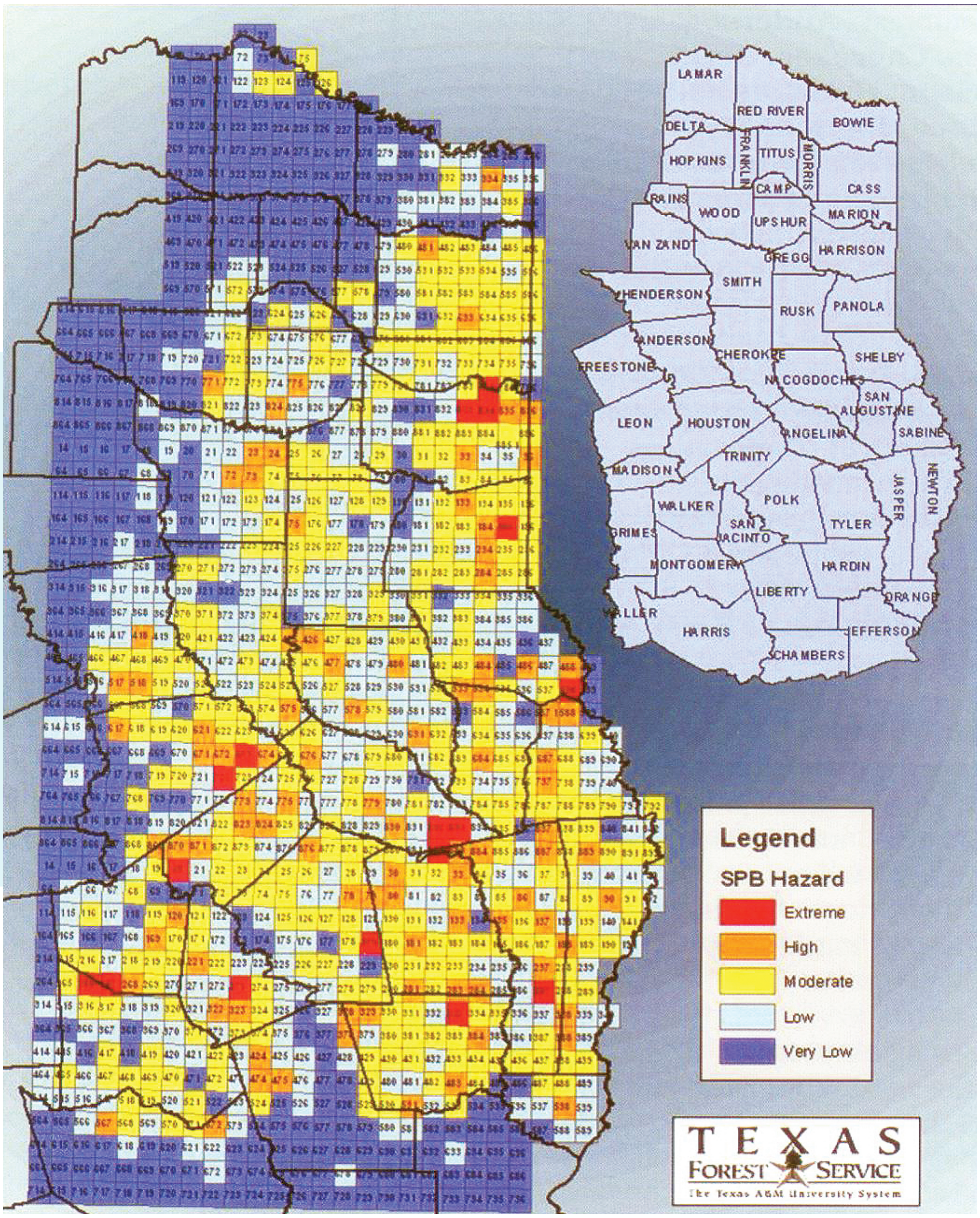

Figure 22.2—Map of categorical risk in East Texas used for determining eligibility to Texas Forest Service cost-share thinning program. The map is for 1996 and derived using work outlined in Billings and others (1985). Ratings from the map form the first component of assessing eligibility for funds (stands must be located in at least a moderate-hazard block). The second component is based on a more detailed appraisal of a particular stand. (Taken from document TFS 3/6/5000)

characteristics of the specific stand. Both models have strong ties to the scientific risk literature but have also been presented in a way that makes them easy to use and understand. For both the Texas Forest Service and small private foresters (nonindustrial private foresters) who use the model, the goal and purpose of the risk analysis is very clear: to determine whether a stand reaches a predetermined risk criteria that qualifies it for Federal dollars. Irrespective of its predictive accuracy, it could be argued that the benefit of this model is that it facilitates effective communication between landowner and the Texas Forest Service, which in turn leads to efficient decisionmaking.

During outbreaks, especially on Federal lands where full-time foresters are available, the focus of SPB management turns to the control of infestations rather than prevention. While infestation probabilities may be relatively small (see previous section), the scale of the forest landscape ensures that large numbers of spots may be detected in relatively short periods of time. So as an outbreak develops, the net result is an overwhelming number of infestations, often in remote areas. In addition, the extended time periods between outbreaks may result in foresters with limited SPB experience or expert knowledge having to visit, assess, and ultimately make decisions about these infestations. These decisions center on control of infestations, salvage of dead timber, and restoration of the damaged stands, all of which are dependant on future infestation growth. These decisions might involve estimates of direct economic damage, whether there is a possibility that an infestation will grow and cross an ownership boundary, presenting possible legal problems, or whether the infestation is likely to impact especially high value or highly protected trees such as red-cockaded woodpecker colonies or seed orchards. Under these situations, widely distributable, quantitative, and easy-to-use infestation growth models provide valuable decision support tools.

Two such models are widely used—the Texas Forest Service spot growth model (Figure 22.3) and the Arkansas Hog Model. The advantage of the former, based on work by Hedden and Billings (1979), lies in its simplicity. Using the basal area of the stand and the number of actively infested trees as the only input variables (both rapidly available by observation), it estimates the expected number of trees killed after 30 days. In addition, the model itself is simple to

TABLE 1

Additional Timber Losses To Be Expected From Spot Growth

Over 30 Days During Summer in East Texas[1]

Number of Active Trees At Day 0[2]		Total Stand Basal Area (ft^2 /acre) 20-60	70-110	120-160	170-210
		Predicted Values at Day 30			
5	Additional tress killed[3]	0	0	0	0
	Trees remaining active[4]	≤ 1	≤ 1	≤ 1	≤ 1
10	Additional tress killed	0	0	2	5
	Trees remaining active	≤ 2	≤ 2	4	7
20	Additional tress killed	0	5	12	18
	Trees remaining active	≤ 4	9	16	22
30	Additional tress killed	2	12	21	30
	Trees remaining active	8	18	27	36
50	Additional tress killed	9	24	39	54
	Trees remaining active	18	33	48	63
75	Additional tress killed	16	39	62	84
	Trees remaining active	30	53	76	98
100	Additional tress killed	24	54	84	115
	Trees remaining active	43	73	103	134

[1]To be used for evaluating spots in East Texas during months of June-October only.

[2]Number of stage 1+ stage 2 trees present when spot growth prediction is made.

[3]Predictions for "additional trees killed" derived from Texas Forest Service spot growth model (based on 1975 data):

$$ATK = [(0.000202\ IAT \times TBA) - 0.2211] \times 30$$

where ATK = number of additional trees killed by day 30

IAT = number of active trees at day 0

TBA = total basal area in ft^2/ acre

[4]Predictions for "trees remaining active" (TRA) based on SPB developmental rate of 37days and formula:

$$TRA = ATK + \frac{7}{37}(IAT)$$

Figure 22.3—Excerpt from Texas Forest Service Leaflet (Circular 249) describing how to calculate risk (spot expansion) for stands with currently active infestations.

use and easy to distribute to foresters faced with active infestations. The limitations of the model are that it is specific to East Texas, although other models could easily be created for other regions, and that it presents a rather simplistic approach to estimating the likely trajectory of the infestation. The Arkansas Hog Model is by contrast a more complex, mechanistic-based model of population growth that provides estimates of infestation growth for any region in the South and can be distributed as a stand-alone PC-based or Web-based program (Stephen and Lih 1985). Again, inputs to the model are relatively simple, easily observable site characteristics, and outputs are average projections of infestation growth based on a validation of the model against independent data.

Probably the most ambitious and largest practical forestry risk assessment exercise is currently being conducted as an ongoing process in order to assess risk for the entire contiguous United States and Alaska (at a resolution of 1 km^2) and for every major forest pest and disease including the SPB. The stated goal of this risk assessment, undertaken as an ongoing process by the Forest Health Monitoring (FHM) Program of the USDA Forest Service, is to provide a strategic assessment for risk of tree mortality due to major insects and diseases. Specifically, one of the major objectives of the program is to "construct a risk modeling framework such that the resulting products may be easily linked with other risk mapping efforts (e.g., threat of wildland fire)" and in accordance with five general principles:

1. An integrative process that includes multiple risk models
2. A transparent and repeatable risk assessment process
3. Scalability allowing risk to be assessed at different spatial scales as more data and models become available
4. A procedurally efficient and straightforward risk assessment process that ensures the project is both realistic and provides outputs that are readily interpreted by a variety of stakeholders
5. A standardized approach that allows comparisons across geographic regions and for different threats

Crucially, the project provides an explicit definition of risk based on the principle that any forest experiences a background level of tree mortality and that levels above this constitute unacceptable damage. They define damage as follows:

"…our threshold value for mapping risk of mortality is defined as the expectation that, without remediation, 25 percent or more of standing live BA greater than 1 inch in diameter will die over the next 15 years (between years 2005 and 2020) due to insects and diseases."

Their definition of total risk and the risk index that they actually use is:

"…risk is often composed of two parts: the probability of a forest being attacked and the probability of resulting tree mortality, referred to as susceptibility and vulnerability, respectively (Mott 1963). Assigning the probability of insect and disease activity to specific locations requires data that is frequently lacking. Therefore, a probabilistic assessment was not undertaken for the 2006 risk mapping project, and we define risk as the potential for harm due to exposure from an agent(s)."

The risk assessment outputs are maps detailing the expected basal area loss per 1 km x 1 km grid (see Figure 22.4 for the map detailing SPB damage). These maps provide a visually appealing overview for forest managers interested in the aggregate health of the forest from a national, State, or county scale. The upfront definition of risk and the resolution of the maps are ideally suited to strategic decisionmaking and allow the results to be readily interpreted. For example, the maps show potential for damage based on site characteristics rather than full expectations of damage. But since the maps are designed to show the likelihood of damage over a 15-year period (a time scale long enough that infestations are likely to occur), it could be argued that this measure is an effective surrogate for actual risk, and the decisionmaking process is likely to benefit from this simplicity. Although the resolution of the FHM study is not designed to be particularly useful for individual landowners, eventually the decisions made using such outputs are likely to cascade down to individual stakeholders. For example, the cost-share program discussed earlier requires effective decisionmaking in order that adequate Federal funds can be allocated to the administering States.

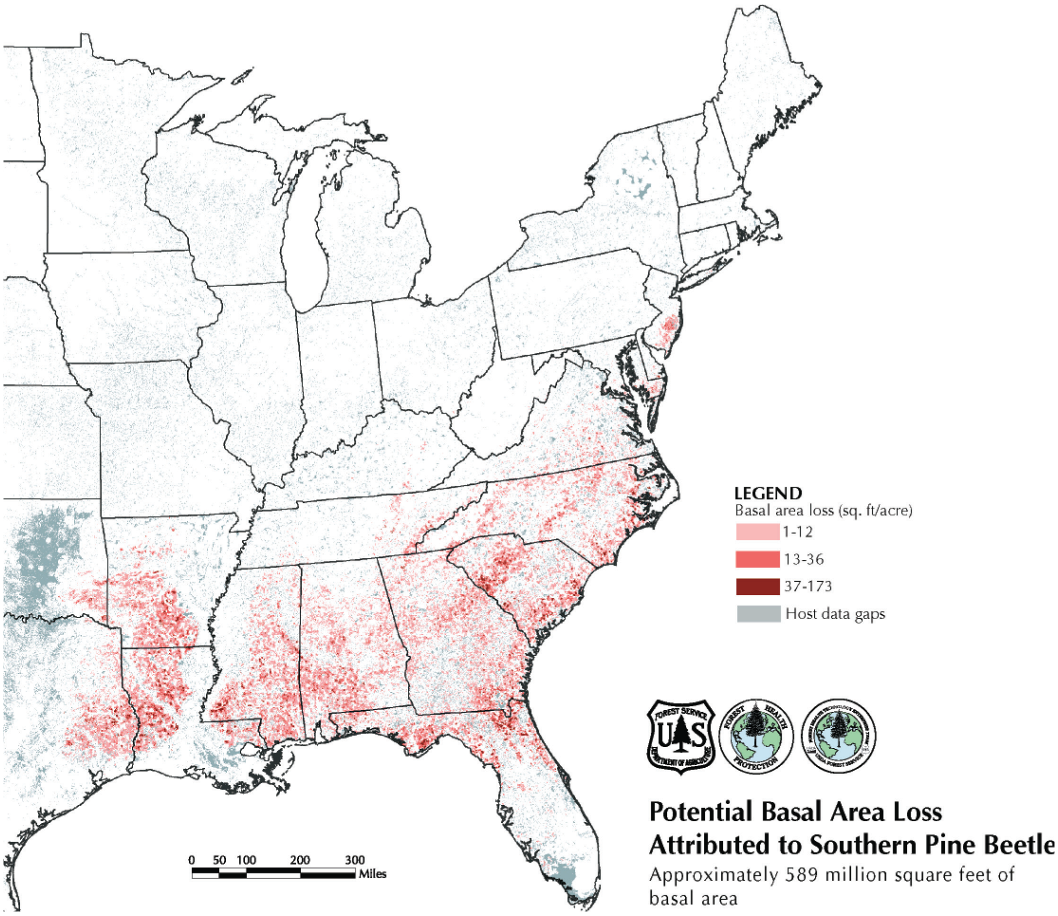

Figure 22.4—Strategic map of expected losses to SPB over a 15-year period at a resolution of 1km x 1km. (map courtesy of Krist and others, in press)

22.4. CONCLUSIONS

Forest management is driven by the value of forest ecosystems that can be impacted by a number of disturbances, including the SPB. Management of the SPB is complicated by its wide geographic range and unpredictability, and the extensive nature of forest ecosystems. This review suggests that it is not possible to predict exactly where SPB damage will occur, but knowledge exists that can be used to identify which areas of the forest are most likely to be damaged, and how much damage can be expected. The goal of risk assessment is to assimilate this knowledge and provide outputs that characterize this uncertainty and enable forest managers to effectively manage the SPB.

A large body of research has shown that certain site and stand characteristics predispose trees to attack. These include the silviculture of the stand (particularly the density and radial growth of trees), damage events (for example, lightning, logging damage), and site characteristics such as slope and drainage. Understanding the role of each factor allows management options to be identified that can be employed in order to minimize risk. Effective decisionmaking also requires estimates of the total amount of damage that one might expect under different management scenarios. These estimates allow an assessment of whether the cost of management actions will be offset by reductions in risk. They also inform forest managers of the potential problems caused by the SPB—it could be argued that SPB damage is more palatable if risks are known up front. One finding of this review is that more emphasis is currently placed upon minimizing SPB damage rather than providing outputs that allow complete risk management.

During outbreaks, the probability of even high-risk stands becoming infested is relatively low (between 0.01 and 5 percent per outbreak). These low infestation probabilities suggest that relationships between measurable stand conditions and infestation probabilities are relatively weak. Models for the growth of infestations (i.e., the severity of an infestation) are less common, but also suggest inherent unpredictability. Explanations for this, and the practical consequences for individuals tasked with managing the forest, have been discussed in previous sections. This unpredictability also has considerable implications for those in charge with managing and contributing to the risk assessment process. In many ways, this unpredictability emphasizes why objective, communicable risk assessments are so important. It is argued that without organized, well-funded approaches to risk assessment, individual forest managers are unlikely to be able to attain an unbiased, objective, and accurate view of SPB risk:

1. Outbreaks are periodic and relatively rare, so that most individuals will experience few during a lifetime.
2. Individuals are most likely to gather experience and knowledge from observations in their own stands. As the literature shows, it is inherently possible that a poorly managed stand will escape SPB damage and conversely that a well-managed stand will incur damage.
3. An objective assessment of risk depends upon balanced information of both infested areas and those that escaped infestation.
4. The unpredictability of the SPB ensures that accurate and objective assessments require considerable amounts of data. It is unlikely that an average forest manager will have the resources to make these unbiased observations.

Considering the unpredictability of the SPB, it could also be argued that without these risk assessments and the objectivity they provide, it would be difficult to formulate effective plans for managing SPB damage. For example, since the initiation and growth of an infestation in one area of the forest may lead to damage elsewhere, the SPB is most commonly viewed as a problem that affects human communities rather than just isolated individuals (Coulson and Stephen 2006). Although preventative management (e.g., basal area reduction) cannot guarantee zero damage, it may considerably reduce total damage at the regional scale. In other words, although the unpredictability and spatiotemporal patterns of the SPB may always lead to winners and losers, a community-level approach to SPB management can at least attempt to minimize the number of individuals affected by the SPB. In addition, the SPB is just one of many threats to forests. Like the SPB, most of these (e.g., fire, hurricane, and other biotic agents) are unpredictable and ideally suited to risk assessment. As defined in this chapter, risk involves not just the pattern of SPB damage, but also concepts and quantifications of the damage, both economic and sociological, caused by the SPB. As human interests encroach further into forested areas, they may also affect the values attributed to these forests and the amount of risk people are willing to accept. This is likely to drive increasingly critical decisionmaking that involves an objective, comparable evaluation of all potential forest threats.

These factors make the development of objective, scientific SPB risk assessments essential. The challenge for ecologists and risk assessors is to develop novel models and assessments that address the current and changing needs of forest managers. This depends on continued efforts to collect appropriate data, and the development of modeling methodologies that assimilate this information into useful risk indices and decisionmaking tools.