Review of Methods for Developing Regional Probabilistic Risk Assessments, Part 2: Modeling Invasive Plant, Insect, and Pathogen Species

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Abstract

We reviewed probabilistic regional risk assessment methodologies to identify the methods that are currently in use and are capable of estimating threats to ecosystems from fire and fuels, invasive species, and their interactions with stressors. In a companion chapter, we highlight methods useful for evaluating risks from fire. In this chapter, we highlight methods useful for evaluating risks from invasive species.

The issue of invasive species is large and complex because there are thousands of potential invasive species and constant movement of new and established plants, plant material, pests, and pathogens. Adequate data are not always available to support rigorous quantitative modeling of the different stages of invasion. However, even a semiquantitative rule-based approach can help to identify locations that contain host species susceptible to specific pathogens or insect pests, and where propagules are more likely to enter based on the current locations of the invasive species, ports of entry, and methods of spread. Predicting long-distance movement is much more difficult, as such events are rare, often poorly understood, and are often influenced by human behavior. Even so, published methods to make probabilistic predictions of pest establishment could be expanded to provide quantitative estimates of spread beyond an initial port of entry. Many invasive species are transported along roads, and so road networks provide some information about the likelihood of introduction into a new region.

Models based on fundamental biological and physical processes, such as population demographics and movement of organisms, can be more robust than purely statistical approaches. Process-based models may better support extrapolation beyond the range of available or historical data because they use predictor variables that represent physical and biological processes. However, even simple correlative approaches may be useful to quantify the overlap in spatial distribution of stressors and ecological receptors as a screening-level analysis. Furthermore, if predictors are chosen carefully, they may represent important processes. For example, data on nonindigenous species may be quite useful for predicting the occurrence of much rarer invasive species because the correlation is based on the key processes of human-influenced transport, establishment, reproduction, and dispersal of propagules. Ecological niche-modeling approaches are useful because they can use data from museum collections in other countries to make estimates of potential new range areas in the United States. Other spatial data such as road networks may also be useful to predict the number of nonindigenous species or presence of a particular species. Such relationships may also support extrapolation to future conditions if there will be more roads or a higher traffic volume.

As for any regional stressor, the use of multiple models and a weight-of-evidence approach would help to increase confidence in predictions of ecological risks from invasive species. Two approaches to predicting the risk of Asian longhorned beetle (*Anoplophora glabripennis* Motschulsky) throughout U.S. forests make quite different predictions because they focus on different stages in the process of establishment and spread, thus combining such approaches should result in more robust predictions. Invasive species management should be addressed at multiple spatial scales, including reducing importation of new species at border crossings and ports, national and regional mapping of locations of invasive species, methods to reduce long-distance transport, and methods to reduce local movement.

Keywords: Ecological risk assessment, invasive species, probabilistic risk assessment, regional risk assessment, risk analysis.

Introduction

This review provides an overview of issues in probabilistic risk modeling at the regional scale and suggestions for productive directions for future risk assessments and research. Invasive nonindigenous species are a serious and increasing threat to many ecosystems throughout the United States (NRC 2002, Pimentel 2005). For example, invasive species are implicated as threats for more than half of all endangered species in the United States (Wilcove and others 1998). Invasive species are also altering fire regimes, hydrology, nutrient cycling, and productivity of ecosystems in the Western United States, particularly rangelands and riparian areas (Dukes and Mooney 2004). Plant species such as yellow star-thistle (*Centaurea solstitialis* L.), other Centaurea species, and cheatgrass (*Bromus tectorum* L.) have overtaken large areas of native ecosystems in the Western United States (LeJeune and Seastedt 2001). Leafy spurge (*Euphorbia esula* L.), knapweeds (*Centaurea* sp.), tamarisk (also known as salt cedar, *Tamarix ramosissima* Ledeb.), nonnative thistles, purple loosestrife (*Lythrum salicaria* L.), and cheatgrass are some of the most severe problems on national forest lands. For example, the number of counties in Washington, Oregon, Montana, and Wyoming where yellow star-thistle has been found has been increasing exponentially during the last 100 years (D'Antonio and others 2004). Furthermore, the number of new exotic species has increased roughly linearly over this time period, reaching a total of nearly 800 by 1997 (D'Antonio and others 2004). Annual costs of selected nonindigenous species in the United States have been estimated at $120 million (Pimentel and others 2005). However, this estimate does not account for all effects of invasive species on rangelands and forests (Dukes and Mooney 2004), and it is clear that such costs are substantial. Despite the difficulty in quantifying economic damage, there is substantial evidence suggesting that invasive species have many deleterious effects in ecosystems in the Western United States, and that improved management of invasive species in wildlands is crucial (D'Antonio and others 2004). For example, tamarisk alone has been estimated to cost $133 to $285 million per year (in 1998 U.S. dollars) for lost ecosystem services including irrigation water, municipal water, hydropower, and flood control (Zavaleta 2000).

Various aspects of invasive species biology and ecology, as well as policy and management issues (NRC 2002), are addressed in many published reviews. We will review briefly some key issues, but the focus in this piece is on modeling methods suitable for spatially explicit probabilistic risk assessments for invasive species. This chapter, and a companion chapter addressing fire (Weinstein and Woodbury, this volume), present results of a project sponsored by the U.S. Department of Agriculture (USDA) Forest Service, Western Wildland Environmental Threat Assessment Center during its development; but these results should not be construed to represent the views of the center nor its personnel. The overall goal of our project was to identify promising methods for analyzing ecological risks to forest, rangeland, and wildland ecosystems from multiple stressors. The results of such risk analyses are intended to provide information useful for strategic planning and management of wildlands including national forests. The specific goal of this chapter is to identify modeling approaches suitable for making spatially explicit, probabilistic estimates of ecological risks from invasive plant, insect, and pathogen species throughout large regions such as the Western United States. Such modeling approaches ideally should be capable of:

1. Calculating risk of a detrimental environmental effect.
2. Using spatially heterogeneous environmental data to drive calculation of risk at different points throughout a region. Spatial scales of interest include landscape, sub-State region, State, region of the United States, or the entire conterminous United States.
3. Relying primarily on available regional (in United States, state or multi-State) or national data.
4. Being useful for many species, not just a single invasive species.
5. Modeling effects of interaction among multiple stressors.
6. Modeling effects of changes in environmental conditions in the future.

We review selected modeling approaches relevant to the goals listed above, and more detailed analyses of specific aspects of invasive species assessment and management are provided by other chapters within this broader work.

Stages of Invasion and Risk Assessment Frameworks

This section provides an overview of the stages of the invasion process, key factors that affect these stages, and different frameworks that can be used to assess risks due to invasive species. The process by which a nonindigenous species becomes an invasive species can be divided into the following five stages:

1. Uptake/entry into transport system
2. Survival and transport to the United States via land, air, or water, with or without vectors
3. Initial establishment—survival and reproduction
4. Local dispersion
5. Widespread dispersion

Three classes of key factors influence the likelihood that a potential invader will pass through each stage: (A) propagule pressure, (B) physicochemical requirements of the potential invader, and (C) community interactions (Colautti and MacIsaac 2004). However, even successful modeling of all stages of the invasion process still does not address the likelihood or degree of damage caused by the invasive species. For this purpose, an ecological risk assessment approach is required.

The topic of invasive species has begun to be addressed by practitioners of ecological risk assessment (Andersen and others 2004a, 2004b; Stohlgren and Schnase 2006). Andersen and others (2004a, 2004b) reviewed the regulatory framework for invasive species in the United States and some of the issues in extending the approach to ecological risk assessment (originally developed for contaminants) in order to address biological stressors such as invasive species. They also provide information about a series of articles of the journal "Risk Analysis" that report the results of a joint workshop between the Society for Risk Analysis Ecological Risk Assessment Specialty Group and the Ecological Society of America Theoretical Ecology Section. In addition, they identify research needs for this field. Of relevance to this chapter, they suggest that "Spatially explicit, multiscale decision-support systems will contribute to better decisionmaking through enhanced credibility, an explicit and direct relationship with managing for sustainability, and explicit illustration of trade-offs and the cost of inaction." Presented in one of the articles in this series is a model of establishment risks for Asian long-horned beetle (*Anoplophora glabripennis* Motschulsky) introduction via solid wood packing materials (Bartell and Nair 2004). This approach estimates both the probability of establishment at the port of entry and the probability of spread based on environmental factors, host availability, and traits of the invasive species. Uncertainty in key parameters is investigated by means of Monte Carlo analysis. Additionally, there is investigation of the efficacy of different management techniques. Integration of quantitative risk analysis and quantitative analysis of management options within a single analytical framework is much too rare and should be applied more widely. Another article in this series describes how the conceptual model in the relative risk model can be applied to predict the effects of invasive species (Landis 2003). This approach is promising in that it is capable of addressing multiple stressors simultaneously at the regional scale by means of a ranking procedure. Although complete risk assessments are not reported in this article, it illustrates how invasive species risk can be analyzed at the regional scale in the context of multiple stressors and multiple endpoints. A case study of this approach has been implemented for a European green crab (*Carcinus maenas* L.) for a region of Washington State (Colnar and Landis 2007).

Transport to the United States and Within U.S. Regions

Most exotic plant species have been introduced to the United States intentionally, whereas most insects and pathogens have entered the United States unintentionally (Mack and Erneberg 2002). Global travel and trade have increased the amount of plant material, wood, and wood products moving into U.S. ports, increasing the likelihood of introduction of invasive plants, insects, and pathogens. By 2020, it has been predicted that more than 100 new

insect species and 5 new plant pathogens will become established (Levine and D'Antonio 2003). A particularly high-risk pathway for forest insects and pathogens is importation of raw logs (Tkacz 2002). As an example for the Pacific Northwest, surveys of ports, port areas, mills and businesses known to have received or handled imported wood or wood products from 1996 to 1998 found seven species of wood-boring beetles from Asia, Europe, and the Eastern United States (Mudge and others 2001). For the United States as a whole, inspections of all types of products in four cargo pathways at ports and border crossings found the highest rate of insect introductions in refrigerated maritime cargo, with 1 new insect species found in every 54 inspections (Work and others 2005). It was estimated in this study that fewer than half of such new species are detected, and 42 insect species may have become established from 1997 to 2001. These species do not necessarily pose a high risk of widespread infestation or damage, but they do indicate that exotic species are entering the United States at an alarming rate. Many of the issues of invasive species transport and establishment from other countries to the United States also apply to establishment of new populations owing to long-distance transport of invasive species among regions in the United States. Gypsy moth (*Lymantria dispar* L.) is an example species known to cause severe infestation and damage in Eastern U.S. forests (Liebhold and Tobin 2006). Gypsy moth has been long established in the Eastern United States but has been prevented from establishing, to date, in the Pacific Northwest owing to surveillance and eradication efforts (Hayes and Ragenovich 2001).

To manage invasions and reduce risks, it is vastly more cost-effective to prevent establishment, or eradicate an invasive species as soon after entry as possible (Simberloff 2003, Stocker 2004). However, most invasive species are difficult to locate and may not appear to present any significant risk to ecosystems until they have become well established, often many decades after introduction. Thus, most management and control efforts focus on severe known problems rather than preventing future severe problems. Also unfortunately, it is difficult to predict which nonindigenous species will become invasive, and which invasive species will become severe problems (Smith and others 1999). A number of initiatives have been undertaken in the United States to address various aspects of invasive species monitoring, risk assessment, and management owing to the severity of problems caused by invasive species.

Existing National Invasive Management Programs

A number of international, national, and regional efforts are underway to attempt to reduce the risks posed by invasive species. Some of these efforts for the United States are discussed briefly below, with a focus on programs related to forest and rangeland ecosystems. It is beyond the scope of this review to discuss all international programs that may provide valuable information for invasive species in the United States. However, some sources of global information are mentioned in the subsequent section on invasive species databases.

The National Invasive Species Council (NISC) consists of eight Federal departments and was formed in 1999 by Executive Order 13112. The NISC 2001 National Management Plan called for development of a risk analysis system for nonnative species by 2003. The NISC is intended to provide a gateway to information, programs, organizations, and services about invasive species. Their Web site (http://www.invasivespecies.gov) provides information about the impacts of invasive species and the Federal government's response, as well as select species profiles and links to agencies and organizations dealing with invasive species issues.

The USDA Animal and Plant Health Inspection Service (APHIS) protects not only agricultural but also forest, rangeland, and wetland ecosystems. APHIS works closely with the USDA Forest Service and the U.S. Department of the Interior's Bureau of Land Management, National Park Service, and Fish and Wildlife Service. APHIS conducts risk assessments with a dual mission to promote international trade and prevent invasive species that may cause serious harm from entering the United States. Some APHIS activities focus on protecting and managing endangered species as well as migratory bird populations. APHIS maintains the Port Information Database, and there is great potential to strengthen and make broader use of this

database for understanding the pathways taken by invasive species entering the United States (NRC 2002).

The USDA Forest Service, working in conjunction with Federal, State, tribal, and private partners, has developed the Early Warning System (EWS) to detect and respond to environmental threats to forest lands in the United States. The EWS comprises many existing programs, along with new initiatives such as the Western Wildland Environmental Threat Assessment Center and the Eastern Forest Environmental Threat Assessment Center. The EWS addresses potential catastrophic threats such as insects, diseases, invasive species, fire, weather-related risks, and other episodic events. The system is intended to:

1. Improve understanding of the crucial elements involved in early detection and response to environmental threats.
2. Help identify and remedy weaknesses in the current system of early detection and response.
3. Aid for strategic planning and resource allocation.

There are many groups both within and outside the Forest Service that participate in the process of detecting and responding to threats to forests. Further information about some component groups that conduct regional risk analyses is presented in other chapters in this volume. Further information about the EWS is available at the following Web site: <http://www.fs.fed.us/foresthealth/programs/early_warning_system.shtml>.

The National Aeronautic and Space Administration (NASA) and the U.S. Geological Service (USGS) are developing a National Invasive Species Forecasting System (ISFS) for the management and control of invasive species on Department of Interior and adjacent lands. The system provides a framework for using USGS's early-detection and monitoring protocols and predictive models to process remote sensing data from the Moderate Resolution Imaging Spectroradiometer (MODIS), the Enhanced Thematic Mapper, and the Advanced Spaceborne Thermal Emission and Reflection Radiometer as well as commercial remote sensing data. The goal is to create on-demand, regional-scale assessments of invasive species patterns and vulnerable habitats. Additional information can be found at the following Web site: http://bp.gsfc.nasa.gov/. This approach has recently been used to predict the relative suitability of all areas in the conterminous United States for tamarisk, an invasive woody shrub (Morisette and others 2006). This analysis is reviewed below under the heading of USGS and NASA Invasive Species MODIS-Regression methodology.

Within the USDA Forest Service, the establishment of the two Threat Assessment Centers is a key part of the strategy for improving the management of invasive species. These efforts build upon ongoing programs and projects such as the Forest Inventory and Analysis Program (including Forest Health Monitoring) and Forest Health Protection. Further information about the strategies of these agencies for invasive species management is provided at the following Web site: http://www.off-road.com/land/invasive_species_strategy.html. Recommendations for control of invasives in rangelands are provided at the following Web site: http://www.fs.fed.us/rangelands/ecology/invasives.shtml

The USDA Forest Service's Forest Health Technology Enterprise Team (FHTET) is using an expert opinion approach to model risks of invasive pests and tree pathogens at the national scale for national strategic planning purposes. Potential tree mortality risk is modeled based on expert opinion, forest inventory data, and other GIS (geographic information system) data (Marsden and others 2005), also see the following URL: http://www.fs.fed.us/foresthealth/technology/products.shtml. Further discussion of this approach is presented below under the heading of "FHTET national risk map."

Availability of Spatial Data

Many kinds of regional data may be useful for developing regional probabilistic risk assessments, including land cover and land use data, transportation networks (e.g., roads and trails), hydrography, climate, digital elevation models, etc. Many such databases are available in GIS format from the National Atlas, which also includes data on selected invasive species (http://www.nationalatlas.gov/atlasftp.html). Data on land use is available from the National Land Cover Characterization database that is being compiled across

States as a cooperative mapping effort of the Multi-Resolution Land Characteristics Consortium. Landcover databases are being developed by bioregion based on remotely sensed imagery acquired from 1999 to 2003 and are complete or nearly complete for most portions of the United States, including the West Coast and much of the Southeast (http://www.mrlc.gov/mrlc2k_nlcd.asp). It is beyond the scope of this review to discuss all of these types of data, or even all types of databases specifically on invasive species, but a brief overview of invasive species survey data is presented below.

At the global scale, the Global Invasive Species Information Network is developing an online registry of data sets related to nonnative species (Simpson 2004), and ongoing efforts are being made to develop linkages among national and multicountry invasive species databases (Simpson and others 2006). The Global Invasive Species Programme (Mooney 1999) provides an online list of invasive species databases, including those covering the conterminous United States, Alaska, and Hawaii (http://www.gisp.org/links/index.asp). In the United States, a survey was undertaken recently to identify data sets of nonnative species at county, State, region, national, and global scales (Crall and others 2006). Based on a literature survey, Internet search, and responses from surveys sent to 1,500 experts, a total of 319 data sets were identified, and metadata were collected for most data sets (79 percent). Of the total, 57 percent are available online (see the following Web site for further information: http://www.niiss.org). Categories of data sets for which metadata are available consist of the following: 77 percent cover vegetation, 38 percent cover vertebrates, 77 percent cover invertebrates, 14 percent cover pathogens, and 9 percent cover fungi. Note that these percentages sum to greater than 100 percent because some data sets cover multiple taxa or categories. The scale of data sets for which metadata are available are as follows: 33 percent are at the county scale, 20 percent at the State scale, 17 percent at the multi-State regional scale, 15 percent are national, and 14 percent are global. Although this number of data sets is encouraging, the authors note that only 55 percent of the data sets have a quality assurance and quality control procedure, suggesting that the accuracy of many data sets may be questionable or undetermined.

Other sources of data useful for regional assessments of invasive species are databases developed by the Forest Inventory and Analysis (FIA) Program of the USDA Forest Service (http://fia.fs.fed.us/). The FIA Program collects data for all land meeting a specific definition of forest land in three phases. Historically, Phase 1 has been based on aerial photography, but now satellite remote sensing imagery is being used. Phase 1 points are used to identify forested and nonforested locations. Phase 2 includes ground measurements such as tree species, height, diameter, disturbance, and stand age on more than 100,000 stratified sampling plots across the country. Historically, the focus was on timber resources that are available for potential harvest, but during recent decades there has been increased emphasis on a broader suite of forest characteristics including forest health and invasive species. In particular, Phase 3 sampling is done on a subset of plots to determine the species, abundance, and spatial arrangement of all trees, shrubs, herbs, grasses, ferns, and fern allies (horsetails and club mosses). This Phase 3 sampling was begun as a separate program called Forest Health Monitoring but is now administered through the FIA Program. As an example, a pilot study collecting Phase three data on plots throughout Oregon found at least 1 nonnative species on 70 percent of all forested plots, and 20 percent of plant cover was nonnative in one of 10 forested plots (http://earthscape.org/r1/ES16479/pnrs_science%20update.pdf; note: membership is required to access this Web site, but free trial membership is available). In addition to data specifically on invasive species, the Phase 2 FIA data are a valuable source of vegetation data because they have been collected in statistically designed surveys for decades. Information on forest type, stand age, and disturbance history are available and can be used in conjunction with data on invasive species to predict vulnerability of forest stands to invasion. Such an approach is underway in the Southern United States (Ridley and others 2006). Phase 2 FIA data are also being used in conjunction with other data to develop regional and national vegetation databases in other research programs including LANDFIRE. See the

topic "Conclusions Concerning the Use of Fire Modeling Systems" in Weinstein and Woodbury (this volume).

Review of Selected Methodologies

In this section, we review selected modeling approaches relevant to the goals listed above in the "Introduction" section. The focus is on invasive species of concern for the Western United States, particularly forest and rangeland ecosystems. Examples were selected to cover a range of analytical techniques with an emphasis on the State or regional scale. In addition, we selected examples of two different methods applied to an invasive pathogen that is the causal agent of sudden oak death disease (*Phytophthora ramorum* Werres, de Cock & In't Veld) and two methods applied to an invasive insect: the Asian long-horned beetle.

Climatic and Ecological Niche Models

The most common and readily applied approaches to predicting the risk of invasive species occupying sites across a large region rely on biogeographical distribution models. These models are based on information about the biophysical factors that limit where a species can survive. Such models are known as bioclimatic envelope models, biogeographical distribution models, and (ecological) niche models. Such models are generally correlative and may be either statistically based or rule based. As applied to invasive species, such approaches typically attempt to map which parts of a region are suitable for the invading species, and suitability is typically based on habitat requirements. For pests and pathogens, the simplest approach is to map the presence or absence of suitable hosts. Such maps are typically developed from available regional data sets, which often provide relevant but not necessarily ideal data for a particular invasive species. Such maps may be useful for strategic planning at the regional scale, but may be of limited use for managing specific areas presuming that the managers of those areas already know where different species occur.

Niche models typically identify habitats for invasive species based on records of their presence at known locations. Such records can be obtained from museum collections such as herbaria, but currently, only 5 to 10 percent of such data are available in electronic form worldwide (Graham and others 2004). To define the niche or bioclimatic envelope, biophysical data for each such location are often extracted from regional databases, usually in a GIS. The most important distinction among such approaches is whether they use absence data in addition to presence data. In other words, whether locations where the invasive species does not occur (absence) are used to define biophysical conditions that are outside of the niche. Either approach is problematic for invasive species because, typically, they have not yet occupied all possible sites. Thus, sites where the species doesn't occur may not necessarily provide information about the species niche or requirements; instead, those may be sites that the invasive species haven't yet reached. Presence and absence data can be obtained from the native region of the invasive species, but the species may have a different niche in the part of the world it is invading, as compared with its native region. However, use of data from the native region may be the only reasonable choice for species that have not become widely established in the United States. Even so, there may be substantial uncertainty in such predictions until a species becomes widely established. For example, an analysis of purple loosestrife (a common invasive species in Eastern United States wetland areas) determined that a reliable prediction of the current nonnative distribution in North America was only possible 150 years after initial establishment (Welk 2004).

Many variations of the niche approach are used to predict the niche of the invasive species including:

1. Simple ranges for factors based on mean climatic variables such as the widely used BIOCLIM and DOMAIN models.
2. Fuzzy rather than crisp calculations of the niche (Robertson and others 2004).
3. The use of spatial statistical techniques and newer computational approaches, such as genetic algorithms and support vector machines.

We have evaluated a few examples of such approaches below, with a focus on the Western United States. For each of these examples, we discuss how they meet the criteria listed above.

GARP Niche Modeling Approach

In this family of approaches implemented in a software tool, the potential range of invasive species is predicted based on point data from the species native home range and spatial data including mean annual temperature, rainfall and elevation (Anderson and others 2003, Costa and others 2002, Godown and Peterson 2000, Peterson 2001, Peterson and Cohoon 1999, Peterson and Kluza 2003, Peterson and others 2003b, Stockwell and Peterson 2002, Underwood and others 2004; also see http://www.lifemapper.org/desktopgarp/). This approach shares many features with other approaches to predict ecological niches based on bioclimatic data, including climate envelope modeling and other methods for niche modeling. All of these approaches assume that bioclimatic predictor variables (for example, mean annual temperature and precipitation) control the native distribution of an invasive species, and these factors will also control the potential distribution in the United States This technique differs from others because it uses a machine learning method (also known as artificial intelligence) named Genetic Algorithm for Rule-Set Prediction (GARP). Based on only 15 to 20 records of locations of a species from its native home range (species input data), the method can predict the potential distribution (home range, or niche) of a species. This approach has been used by its developers to model the niche of both invasive species and noninvasive species. The user needs to provide species input data of known points where the species has been found in its native region. These data should be well distributed throughout the species native range and need to be georeferenced. The user also needs to provide environmental data covering the entire area for which predictions are desired, including mean annual temperature and precipitation (modeled surfaces). Potentially, many other input data could be used such as remote sensing images, but they might need to be available for both native region and the analysis region.

The software used is desktopGARP, which can be downloaded from the following Web site: http://nhm.ku.edu/desktopgarp/. The user selects a type of inferential tool, such as logistic regression, or bioclimatic rules. The input data are then divided into training data and validation data. The software generates pseudodata via resampling, and then iteratively tries a large number of rule sets, continuing either until there is no further improvement in the predictions, or 1,000 iterations. The output from the model is a map of species niche as presence/absence, with some confidence values. Modeling may be done for either counties or for grid cells (pixels). The primary prediction is whether a county or a pixel is contained in the species potential (fundamental) niche. A measure of likelihood is generated by using multiple models, and assigning higher likelihoods to counties or pixels predicted to be included in the niche by multiple models (Peterson and others 2004).

In the following citations, only one predicted value is made per county, although the approach could be extended for finer grain analyses if input data are available at finer scales. The methodology (Peterson 2003) and its use to predict the distribution of four alien plant species in North America for a single point in time (the fundamental niche) are described in the references reviewed herein. Invasive plant species analyzed to date include Hydrilla (*Hydrilla* L.C. Rich.), Russian olive (*Elaeagnus angustifolia* L.), sericea lespedeza (Lespedeza cuneata (Dum.-Cours.) G. Don), and garlic mustard (*Alliaria petiolata* (Bieb.) Cavara & Grande) (Peterson and others 2003a). To predict the spread of Asian long-horned beetle, the GARP approach has been combined with a spatial model of spread originally developed for forest fire (Peterson and others 2004).

The GARP approach has several strengths for the regional risk analysis of invasive species, which are as follows:

1. It has been applied to a number of taxa of invasive and noninvasive species in the United States and elsewhere.
2. A freely available software tool has been developed that implements this approach.
3. Data requirements for this approach are modest.

Most weaknesses of the GARP approach are shared by all niche modeling approaches, which include:

1. Not all of the stages of the invasion process are modeled.
2. Only presence or absence of a species is predicted, not effects of invasive species.
3. Results may be biased, depending on the

source of data and the use of pseudo-absence data (Graham and others 2004).

Other approaches such as support vector machines and generalized additive model (GAM) approaches may be less biased and provide more optimal statistical solutions (Elith and others 2006, Stockwell 2005), but see also Anderson and others (2003) for improving on model selection methods.

FHTET National Risk Mapping Approach

This approach is also a family of related approaches to predict tree mortality risk owing to an invasive insect or pathogen based on expert opinion, forest inventory data, and other GIS data (Marsden and others 2005), and also consult FHTET products Web site: http://www.fs.fed.us/foresthealth/technology/products.shtml). Specifically, predictions are made of the potential basal area loss of susceptible tree species owing to an invasive insect or pathogen. The location of suitable host species is interpolated using inverse-distance weighting based on forest inventory data. A multi-criteria risk ranking model is developed based on expert opinion about the factors that influence pest or pathogen establishment, spread, and tree mortality. An iterative process is used to develop risk maps, so the experts and analysts can alter the weighting of difference factors to adjust the maps to match expert opinion. This approach has been used to predict the potential effect of oak wilt in the North Central States and of wood wasp (*Sirex noctilio* Fabricius) throughout the conterminous United States: (http://www.fs.fed.us/foresthealth/technology/invasives_sirexnoctilio_riskmaps.shtml).

The following are the key required input data and their sources:

1. Principal U.S. ports - Army Corps of Engineers, Waterborne Commerce, Foreign Cargo Statistics.
2. Markets for wood products - Federal Highway Administration, Freight Management and Operations, Freight Analysis Framework, Highway Truck Volume and Environmental Systems Research Institute's (ESRI) polygon data.
3. Distribution centers - National Transportation Atlas Database.
4. Species occurrence and basal area of individual tree species – USDA Forest Service, Forest Inventory and Analysis (FIA), National and New York State Christmas Tree Association Web sites.
5. Road density and distance to road – U.S. Geological Survey, Heterogeneous Distribution Indicator.

Use of this approach requires one or more experts on the pest or pathogen, expertise in the use of FIA data, and expertise in GIS software. The spatial scope is the conterminous Unites States for a single time period. Required software includes ArcView 3.x, Spatial Analyst ModelBuilder (ESRI, Inc.), and IDRISI 32 (a raster GIS software package). Model output includes maps of predicted occurrence based on (1) hosts known to be susceptible and (2) hosts suspected to be susceptible.

For regional and national risk analysis, the approach of mapping factors that influence a stressor and then combining these factors with weightings derived from expert opinion are intuitively appealing and fairly common. This flexible, iterative expert opinion-based approach can be used for virtually any pest or pathogen, and a risk map can be generated fairly quickly because the system is already in place. Other strengths of this approach include the use of national FIA data and the quantification of potential damage in terms of tree mortality. However, the flexible expert opinion-based approach is also a weakness because it is so open-ended, subjective, and difficult to validate. To date, it does not appear that an attempt has been made to determine which environmental factors were actually associated with pest presence, or to quantify uncertainties in GIS layers or predictions. In contrast, a statistical inference approach that made quantitative predictions of pest occurrence would be more useful because it could be better tested against validation data.

Meentemeyer Sudden Oak Death Approach

Meentemeyer and others (2004) used a rule-based function to predict spread of sudden oak death pathogen distribtions

in grid cells (30 by 30 m) throughout California. A prediction was made of the likelihood of presence of the disease based on rules derived from expert opinion and published data on plant species susceptibility, pathogen reproduction, and host climate. This method is focused on evaluating a single risk, the probability of oaks on a given site being infected by *P. ramorum*. More specifically, the method begins with mapping five predictor variables in a GIS and then using a set of rules to determine the risk of infection based on these predictor variables. The predictor variables are host species index, precipitation, maximum temperature, minimum temperature, and relative humidity. Host species index is weighted three times as strongly as precipitation and maximum temperature, which in turn are weighted twice as strongly as relative humidity and minimum temperature. Each variable is classified on a relative index, with host scored on a scale from 0 to 10, precipitation, maximum temperature, and humidity scored from 0 to 5, and minimum temperature scored from 0 to 1. The model was tested against 323 field observations in California. The model generally predicted higher risk for sites where *P. ramorum* is currently present and lower risk for sites where it is currently absent. However, it appears that approximately 20 percent of low-risk sites were infected.

Input data for the model include host susceptibility, pathogen reproduction, and host climate suitability. Like many modeling approaches, this approach requires expertise in GIS and database analysis. The model output is in the form of a map with estimated risk of occurrence of the pathogen at a single time period – movement of the pathogen is not modeled. The spatial scope includes all of California, and the map unit is landscape cell (30 by 30 m). The approach uses the CALVEG database (USDA Forest Service RSL 2003) for vegetation alliance and presence of *P. ramorum* and the Parameter-elevation Regressions on Independent Slopes Model (PRISM) for elevation-based regression extrapolations from base weather stations for climate data, which are available for the conterminous United States (http://www.wcc.nrcs.usda.gov/climate/prism.html).

The method meets the criterion of calculating the risk of detrimental environmental effect by mapping the probability of pathogen occurrence in each forest grid-cell and could be extended to predict the presence of pathogens in smaller regions or pixels. But the focus is assessment of effects over a region, specifically bioregions, rather than at all points within a region. The method meets the criterion of using spatially heterogeneous environmental data to drive calculation of risk at different points throughout the Western United States. Potentially, it could be used to evaluate the risk from a number of stressors, but relationships between habitat conditions and probability of stressor occurrence would have to be developed. Potentially, the method could be extended to consider effects of interaction among multiple stressors, but interaction terms would need to be identified and parameterized in a regression model. The approach does not currently consider the effect of changes in environmental conditions over time.

Unfortunately, no attempt was made to determine which environmental factors were actually associated with disease presence. A statistical inference approach that made quantitative predictions of pathogen occurrence would be more useful because it could be better tested against validation data when they become available. The finding that 21 percent of sites predicted to be low risk, yet were found to be infected, suggests that the model has limited predictive power. This limited power is likely due to data limitations as well as lack of precision in rules and weights applied to them. The investigators do state that they plan to use FIA data to improve the predictions. This study was evaluated because it addressed an important risk factor in Western and potentially Eastern U.S. forests, but use of a method that makes more quantitative predictions would be useful in the future.

Nowak Host Range Approach

This approach predicts potential home range of an (invasive) insect or pathogen of trees by modeling the location of suitable host species based on forest inventory data (Nowak and others 2001, http://www.fs.fed.us/ne/syracuse/Data/Nation/InsectPoten.htm). A model of urban forests (UFORE) is used to predict urban forest composition based on data from a limited number of cities in the United States. Predictions are also made of the amount of tree cover that could be lost owing to tree death and the costs of replacing killed trees.

A simple model of spread (moving outward at a constant rate from one location) was used to predict the length of time required for invasion to occur in each major city. This approach has been used to predict the potential effect of Asian long-horned beetle throughout all urban areas in the United States (Nowak and others 2001), and preliminary predictions have been made for nonurban areas (http://www.fs.fed.us/ne/syracuse/Data/Nation/InsectPoten.htm). Preliminary predictions have also been made for the emerald ash borer (*Agrilus planipennis* Fairmaire) (http://www.fs.fed.us/ne/syracuse/Data/Nation/InsectPoten.htm). The main type of required input is appropriate forest inventory data. Model output is in the form of maps of predicted occurrence based on (1) hosts known to be susceptible and (2) hosts suspected to be susceptible. The model has been used at the scale of the conterminous United States for a single point in time.

One strength of this approach is the use of FIA data in conjunction with a model that has been used for many years. Another strength of this approach is the quantification of damage in terms of economic losses of urban trees. For urban trees, such economic losses are quite high, though for wildlands they will be much lower for an individual tree and much harder to estimate for a forested region. A limitation for regional risk assessment and management is that the focus of the model is urban areas. Another limitation, typical of most niche modeling efforts, is that not all steps in the process of invasive dispersion and reproduction are modeled, and that predictions are primarily of the potential host range of the pathogen, not of effects of the pathogen other than economic losses owing to the death of urban trees.

USGS and NASA Invasive Species MODIS-Regression

In this approach, a logistic regression is developed to predict the suitability of each 1-km pixel as habitat for tamarisk throughout the conterminous United States (Morisette and others 2006). Various ground surveys of tamarisk occurrence were integrated into a single database as presence or absence of tamarisk. Land cover, normalized difference vegetation index (NDVI), and enhanced vegetation index (EVI) were derived from MODIS data products. A discrete Fourier transform was used to model a constant amplitude yearly sine wave to each pixel, and the mean, amplitude, and phase of both NDVI and EVI were used as potential predictor variables along with a fitted parameter for each land cover class in a logistic regression model to predict the likelihood of habitat suitable for tamarisk. The ground data were split into a training set to fit the model (67 percent of data) and a validation set (33 percent of data). The best model included land cover, and seasonal variability in NDVI and EVI. The proportion of correctly predicted observations using a threshold of 0.5 was 0.90. The main model inputs are MODIS data and surveys of tamarisk presence. Because it is a regression procedure, many other input data could be used, such as human population density, trail networks, air temperature, etc. The main model output is a relative ranking of the likelihood of suitable habitat for an invasive species.

This general approach would be useful for regional assessments because it uses remotely sensed data that cover the entire conterminous United States. However, for each invasive species, a large database of ground survey data is required. If FIA or other systematic survey data could be used for this purpose, that would make the approach useful for many more invasive species. A limitation of this approach is that it uses statistical correlation to make predictions, thus it cannot readily predict the effect of future environmental conditions such as changes owing to development, changes in hydrology, or changes in regional or global climate. Other examples of logistic regression to analyze invasive species include multiple species in South Africa (Higgins 1999) and Russian knapweed (*Acroptilon repens* (L.) DC.) in Colorado (Goslee and others 2003).

Dark Invasive Species Spatial Autoregressive Approach

This approach uses spatial statistical analysis to predict the distribution of invasive and noninvasive alien plants throughout all bioregions in California (Dark 2004). Spatial autoregressive (SAR) models were used to assess the relationship between alien plant species distribution and native plant species richness, road density, population density, elevation, area of sample unit, and precipitation. Three predictors were found to be statistically significant for both

invasive and noninvasive plants: elevation, road density, and native plant species richness. The best model (with all predictors) explained about 80 percent of the variance in the number of alien species in each bioregion. Additionally, there was significant spatial correlation for both invasive and noninvasive alien plants. Both invasive and noninvasive alien plants are found in regions with low elevation, high road density, and high native-plant species richness. Spatial data input requirements include a digital elevation model, precipitation (a modeled surface), road networks, native species richness, and occurrence of alien species. Because it is a regression procedure, many other input data could be used, such as population density, trail networks, air temperature, traffic volume, etc. The model has been applied to all of California for a single time, with bioregions as the map unit. Model outputs include maps of the number of invasive and noninvasive alien species by bioregion. The method could be extended to predict the presence of invasive species in smaller regions or pixels.

This general approach would be useful for regional probabilistic risk assessments because it uses widely available data in conjunction with a flexible spatial statistical approach. Additionally, it predicts the total number of nonindigenous (alien) species within a region. This technique could be feasibly extended to predict the probability of occurrence of invasive species based on the occurrence of noninvasive alien species. This would be very useful because noninvasive species were found to be roughly tenfold more common than invasive species for the bioregions. This would be a useful first step for regional risk assessment for large regions such as the Western United States in order to identify areas with higher overall risk for invasive species. The approach could be improved by using more detailed data on vegetation types rather than bioregions. A limitation of this approach is that it uses statistical correlation to make predictions, thus it cannot readily predict the effect of future environmental conditions, such as changes owing to development, changes in hydrology, or changes in regional or global climate. However, it might be feasible to develop statistically based extrapolations from existing data. For example, if the number of nonindigenous species in a region can be predicted based on some measure of the transportation network, or other environmental factor, one could extrapolate to future conditions with more roads or a higher traffic volume. A future scenario of new road development or greater traffic or both on existing transportation networks could be developed based on planned State and Federal transportation projects. This scenario could be used to predict the subsequent increase in occurrence of nonindigenous species and invasive species.

Guo Support Vector Machine Approach

This method uses a type of machine learning algorithm called support vector machine (SVM) in a niche modeling approach to predict risk of occurrence of sudden oak death throughout California (Guo and others 2005). A useful comparison is made of presence-only (one class SVM) versus presence with pseudo-absence data (2-class SVM). Based on their results, the use of pseudo-absence data does not appear to be a good choice for modeling invasive species—they inherently lead to bias because they conflate environmentally determined absence with absence on account of infestation not having occurred yet in a particular location. Input data include 14 environmental variables including mean annual temperature, mean annual precipitation, distance to roads, distance to patches of hosts, and presence of susceptible species. The use of this approach currently requires an analyst with not only GIS skills, but also substantial programming skill. Also, assistance may be needed from algorithm developers to modify code. Model output is a map of the potential location of the invasive species. The spatial scope includes all of California, and the map unit is a 1-km grid cell for a single time. Two regional databases are used as input data: California GAP and climate surfaces from the DAYMET model (http://www.daymet.org/). The software used is LIBSVM, which is a library of generic support vector machine functions developed by Chang and Lin 2001, as cited by Guo and others 2005. In this approach, risk is calculated only as potential presence of the disease. There are some probabilistic components, but many sources of uncertainty are not quantified.

This approach would be useful for regional probabilistic risk assessments because it is a generic machine learning technique applied to niche modeling. Thus, it could be used

for invasive plants, insects, diseases, and possibly other stressors. One-class SVMs appear particularly attractive because they are statistically based and unbiased and theoretically optimum, unlike some other machine learning methods and don't require a lot of model tuning. A weakness of the approach, at least for many potential users, is dependence on a library of computer code functions rather than a more mature and user-friendly software package, and assistance may be required from the library developers to apply the functions in an analysis. This approach also does not account for time, nor does it incorporate spatial processes such as dispersion. It may be difficult to specify weights for each variable. Like all niche models, it is dependent on data quality, and there will likely be issues of spatial support and spatial scaling.

Discussion

The issue of invasive species is large and complex because there are thousands of potential invasive species and constant movement of plants, plant material, pests and pathogens, in addition to established invasive species. It seems clear that the most cost-effective approach is to control invasive species very early in the process of transport from the native range and entry to the United States. This issue has received national recognition as an important threat and should be addressed at the national scale (NRC 2002). Increased international trade is exacerbating the problem, and despite this increase, the budget for APHIS, the first line of defense, has been decreasing in recent decades as a function of the volume of imported material (D'Antonio and others 2004).

Despite the lack of complete data sets and complete information about the biology and ecology of invasive species, it is feasible to develop risk analyses of invasive species at the regional scale that should provide information useful for land managers. Even a semiquantitative rule-based approach can help to identify locations that contain susceptible host species for specific pathogens or insect pests and where propagules are more likely to enter, based on the current locations of the invasive species and methods of spread (for example, Meentemeyer and others 2004, Nowak and others 2001). As discussed above, the use of regional forest inventory data and detailed vegetation mapping based on these and other data provide an important starting point for regional risk assessments of invasive species.

A broad range of niche modeling approaches are useful because they can use data from museum collections in other countries to make estimates of potential new range areas in the United States. Such data provide information about the fundamental niche of the organism, although this information must be evaluated critically by scientists skilled in taxonomy and biogeography and applied with care (Graham and others 2004). The GARP approach would be useful for regional assessments because a software package is available specifically to apply this method to niche modeling. However, other approaches such as support vector machines and GAM approaches may be less biased and provide more optimal solutions (Elith 2006, Stockwell 2005).

As compared to predicting the fundamental ecological niche of a species, predicting the rate of long distance movement is much more difficult because such events are rare, may not be well understood, and may be affected by human behavior. The approach demonstrated recently by Bartell and Nair (2004) to examine pest establishment and spread could be expanded and adapted to provide quantitative estimates of spread beyond an initial port of entry. There is a large body of work in the spatial ecology literature addressing various aspects of the spread of populations and, more generally, the role of space in structuring populations and metapopulations (Tilman and Kareiva 1997). In recent years, there has been an increase in the number of publications using empirical data in conjunction with modeling approaches to predict the spread of invasive plant species. This process is complex because of the rare, but crucial events of long-distance transport, including movement from the native range to the United States. Whereas simple diffusion models may be useful in some instances, the issue of long distance transport by human vectors needs to be addressed (Hastings and others 2005). Some of the methods discussed above included estimates of spread. One such analysis to assess the risk posed by Asian long-horned beetle combined the GARP niche modeling approach with a simple model of spread from likely ports of entry (Peterson

and others 2004). This approach makes predictions quite different from those based on analysis of species host range, as discussed above (see "Nowak Host Range").

Models based on fundamental biological and physical processes, such as population demographics and movement of organisms, generally are preferable to correlative statistical approaches. This does not mean that correlative approaches are not valuable for probabilistic regional risk assessments. They may be useful first steps for regional analysis (for example, to quantify the overlap in spatial distribution of stressors and ecological receptors throughout the Western United States). Correlative models such as that of Dark (2004) may be extended with some confidence beyond the range of available data because they use predictor variables that represent physical and biological processes. For example, the distribution of nonindigenous and invasive species was found to be similar, because both must pass through the same environmental filters or stages. The approach of using data on locations of all nonindigenous species to predict the occurrence of much rarer problem-invasive species may be quite useful because the correlation is based on the key processes of human-influenced transport, establishment, reproduction, and dispersal of propagules. In such cases, statistically based extrapolations from existing data should be quite credible and useful. In addition to extrapolating from all nonindigenous species to only invasive species, future environmental scenarios might be developed to predict future risks. For example, one could extrapolate to future conditions with more roads or a higher traffic volume, if the number of nonindigenous species in a region can be predicted based on some measure of the transportation network (Larson 2003, McKinney 2002) or other environmental factor. A future scenario of new road development or greater traffic or both on existing transportation networks could be developed based on planned State and Federal transportation projects. This scenario could be used to predict the subsequent increase in occurrence of nonindigenous species and invasive species.

Risk assessment for invasive species will be most useful if it helps provide information about the degree of potential harm, or damage. For certain invasive plant species, especially serious and common weeds of crop and rangelands, damage can be quantified in economic terms. However, it can be difficult to quantify the ecological effects of many invasive species, especially for effects on wildlands. For example, it has been assumed that purple loosestrife is a serious threat to wetlands in the Northeastern United States, and considerable effort has been made to eradicate it. However, an analysis of ecological effects found little evidence for damage to wetlands (Hager and McCoy 1998), although one recent publication did find some evidence that it can reduce native plant diversity (Schooler and others 2006). The lack of evidence of severe ecological effects in wildland ecosystems does not mean that such effects don't exist. Rather, such a lack of evidence may indicate a lack of research on wildland ecosystem effects and the difficulty in quantifying such effects in wildland ecosystems as compared to highly managed ecosystems such as agricultural row crops. This difficulty in assessing economic damage of invasive species has been recognized as a key challenge for research (Andersen and others 2004a). Despite the challenge, such efforts may be useful, as they may provide evidence that even large expenditures required for removal of invasive species may provide a valuable economic return. For example, it has been estimated that the costs of eradication of tamarisk throughout the Western United States would be fully recouped within 17 years with continued ongoing benefits beyond that time (Zavaleta 2000).

As for any regional stressor, the use of multiple models and a weight of evidence approach would help to increase confidence in predictions of ecological risks from invasive species. As discussed above, two approaches to predicting the risk of Asian long-horned beetle throughout U.S. forests make quite different predictions because they focus on different stages in the process of establishment and spread. All models have some level of uncertainty both in the data used to drive the model and in the calculations made within the model. A focus on uncertainty as an important type of information is crucial for meaningful assessments of invasive species risk. There is strong evidence of the potential for invasion and damage to occur for certain species such as those already on lists of noxious weeds. The strongest predictor for a species is if that species is already

an invasive species causing substantial damage in another part of the world. For these species, there is generally quite a bit of information about aspects of their life history that are important for predicting risk, such as host range, reproductive potential, and phenotypic plasticity. However, for other species there is little or no information. For example, the causal agent of sudden oak death in California was only discovered because of unusual mortality and morbidity in California live oaks. Investigation revealed a new species; thus, there was virtually no information about the ecology of the species such as host range, climatic requirements, and reproductive potential. Until such information began to be gathered, it was not possible to make any meaningful prediction of invasiveness or ecological risk.

Finally, risk assessments will not be useful unless they provide guidance for management. Land managers could benefit in particular from regional risk assessments that provide information about potential future risks. Invasive species management should be addressed at multiple spatial scales such as:

1. Reducing importation of new species at border crossings and ports.
2. Conducting national and regional mapping of locations of invasive species.
3. Developing procedures to reduce long-distance transport if possible.
4. Developing local procedures to reduce movement of invasive species.

Because many invasive species become established along roadways and trails, it may be easier to locate and eradicate them before they spread. However, costs of eradication can be very high, and the most cost-effective approaches will be at the national and regional scale, rather than the scale of a single national forest. Quantitative approaches to estimate the costs and benefits of management options are needed. The feasibility of estimating such costs has been demonstrated (Bartell and Nair 2004, Zavaleta 2000), but much more work is required. Developing such estimates by bringing together risk assessors and land managers should be considered in developing regional risk assessments that will help focus on key issues for management.

In summary, we offer the following suggestions to be considered when selecting modeling approaches for probabilistic risk assessment for invasive species at the regional scale:

1. Define management options and formulate the risk problem definition at the same time so that predictions will be useful for making management decisions.
2. Ecosystems are spatially explicit, so use spatially explicit data, such as vegetation type, topography, stream networks, and elevation.
3. Use both socioeconomic and ecological information.
4. Do not assume that the initial conditions of a landscape can all be captured by a few regionalized variables because of the large role that site history often plays in shaping future dynamics.
5. Whenever possible, make quantitative predictions of risks rather than using ranks (such as low, medium, and high). Ranked values can lead to erroneous interpretations because it may not be clear what is meant by a high risk and also because of uncertainty about what happens at the boundaries of the rank categories.
6. Quantify important spatial and nonspatial sources of data uncertainty and address these uncertainties in the analysis.
7. Quantify important sources of uncertainty in model equations, including aggregation and scaling issues, and address these uncertainties in the analysis.
8. Whenever feasible, use multiple models based on different approaches and data.

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Pests/Biota

Case Studies

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Developing and Validating a Method for Monitoring and Tracking Changes in Southern Pine Beetle Hazard at the Landscape Level

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Abstract

The objective of this research project is to develop and validate a method for using satellite images and digital geospatial data to map the distribution of southern pine beetle (SPB) habitats across the pinelands of east Texas. Our approach builds on a work that used photo interpretation and discriminant analysis to identify and evaluate environmental conditions suitable for SPB infestation. Because current implementations of Billings and Bryant's method by the Texas Forest Service (TFS) use manual photo interpretation, they are relatively costly, labor intensive, and require sampling. Satellite imagery and geographic information system (GIS) technology present potential means to reduce operational costs and improve accuracy. Here we report the principal results of our work in a pilot area of east Texas, specifically: (1) development and integration of satellite and digital inputs into the Billings and Bryant model, (2) accuracy assessment of model inputs, (3) validation of the model adaptation through comparison of satellite-derived SPB hazard maps to operational maps produced by TFS, and (4) revalidation of the model through comparison of satellite-derived SPB hazard maps to known locations of SPB infestations. Collectively, the results point to the considerable potential of satellite imagery and automated analysis techniques to produce timely, accurate, and cost-effective maps of SPB hazard at the landscape level.

Keywords: *Dendroctonus frontalis*, GIS, hazard rating, remote sensing, risk assessment, satellite data, Texas.

Introduction and Background

The southern pine beetle (SPB), *Dendroctonus frontalis* (Coleoptera: Curculionidae: Scolytidae), is one of the most destructive insect pests of pine forests in the Southern United States, Mexico, and Central America (Thatcher and others 1980). The beetle's range extends from New Jersey to Texas and from New Mexico and Arizona to Nicaragua. Because populations build rapidly during periodic outbreaks and large numbers of trees are killed, this insect generates more concern among managers of southern pine forests than any other insect pest. In the Southern United States, average annual losses may exceed 100 million board feet of sawtimber and 20 million cubic feet of growing stock (Price and others 1998).

Southern pine beetle outbreaks have increased in frequency, severity, and distribution during the past 30 years. Preventive silvicultural practices offer the most promising and long-lasting means of reversing this trend (Belanger and others 1993, Nebeker and others 1985). If pine stands are weakened by drought, flooding, lightning strikes, careless logging, or overcrowding, they become more susceptible to attack by the beetle (Blanche and others 1983, Hicks and others 1980). Mature trees in pure, dense stands have long been considered most susceptible to SPB attack, but, in recent years, unthinned pine plantations have increasingly supported SPB infestations (Cameron and Billings 1988). Trees less than 5 years of age or less than 4 inches in diameter are seldom attacked. Dense pine stands also are more likely to suffer extensive losses from the expansion of established SPB infestations in the absence of direct control (Hedden and Billings 1979).

The most practical approach to minimizing timber losses and avoiding costly short-term suppression projects is to maintain forests in a vigorous, healthy condition (Belanger 1980, Hedden 1978). To manage SPB populations

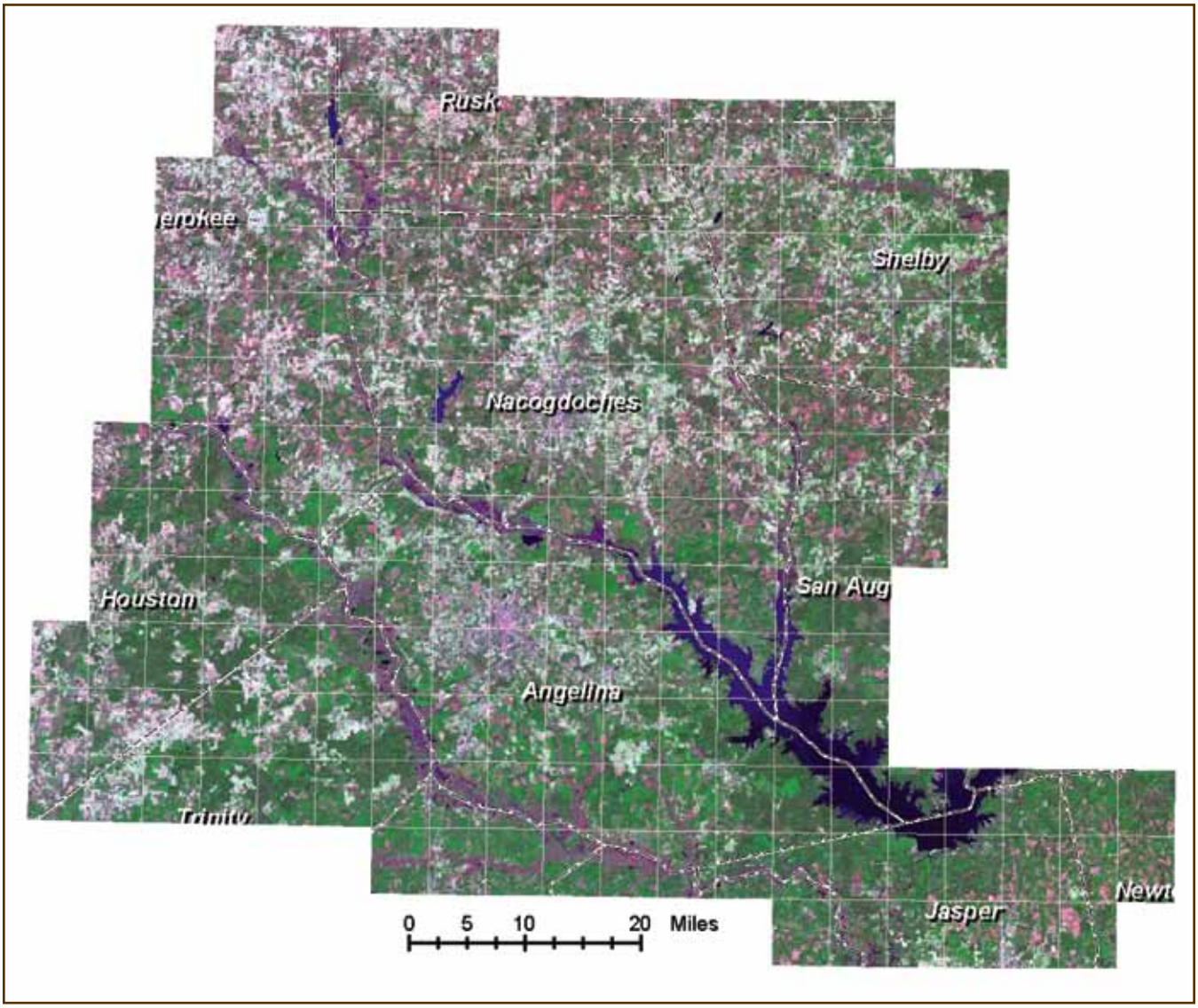

Figure 1—Location of the project area in east Texas. Boundaries of counties and 18,000-acre grid blocks are indicated in white.

more effectively, foresters need reliable means of predicting where infestations are most likely to occur. Once this capability is developed, areas where beetle-caused timber losses are likely can be identified and managed through long-range plans (Peterson 1984), silvicultural manipulations (Belanger and Malac 1980, Belanger and others 1993) or more responsive direct control tactics (Swain and Remion 1981), or all. Several practical stand hazard rating systems have been developed that utilize easily measured stand and site factors (basal area, tree age or height, growth rate in the last 5 years, land form, etc.) to ascertain susceptibility to SPB at the stand level (Hicks and Mason 1982, Hicks and others 1980, Lorio and others 1982, Mason and others 1985). Identification of SPB hazard at the landscape level, however, has received much less attention.

A system for mapping SPB hazard at the landscape level using aerial photography has been developed and implemented by the Texas Forest Service (TFS) on an 18,000-acre grid (Billings and Bryant 1983, Billings and others 1985). The rating system uses conventional photo-interpretive methods to describe host presence, coverage, density, and site conditions within 30-acre photo plots.

Table 1—Independent variables used in the Billings and Bryant (1983) hazard model

Variable	Description
A	Nonhost (open land, hardwoods, water)
B	Young pine (less than 15 years of age)
C	Pine host, < 70 percent coverage, < 80 percent crown closure, other terrain
D	Pine host, < 70 percent coverage, < 80 percent crown closure, bottomland
E	Pine host, < 70 percent coverage, ≥ 80 percent crown closure, other terrain
F	Pine host, < 70 percent coverage, ≥ 80 percent crown closure, bottomland
G	Pine host, ≥ 70 percent coverage, < 80 percent crown closure, other terrain
H	Pine host, ≥ 70 percent coverage, < 80 percent crown closure, bottomland
I	Pine host, ≥ 70 percent coverage, ≥ 80 percent crown closure, other terrain
J	Pine host, ≥ 70 percent coverage, ≥ 80 percent crown closure, bottomland

Twenty circular photo plots, equally spaced in five rows and four columns, provide a 3-percent systematic sample of host conditions within each grid block.

An initial hazard map for east Texas based on 1981-83 aerial photography covered 656 grid blocks (11,808,000 acres) and was validated using subsequent SPB detection records (Billings and others 1985). In 2003-04, as part of the ongoing SPB prevention project, the east Texas hazard map was updated using 1996 color infrared photography. The updated map identified 16 grid blocks (2 percent) as extreme hazard, 92 (12 percent) as high hazard, 291 (37 percent) as moderate hazard, 280 (35 percent) as low hazard, and 117 (15 percent) as very low hazard.

Although the east Texas hazard maps have been valuable for predicting where SPB outbreaks are most likely to occur and for targeting prevention programs, their production process has three limitations that have prevented widespread adoption of this protocol. These limitations are:

- Expense: Creating a SPB hazard map across east Texas (14.3 million acres) requires high resolution color infrared imagery and procedures to digitize and orthorectify the imagery. Furthermore, photo interpretation must be performed by trained technicians. All three requirements are very costly.
- Accuracy: Though the aerial imagery is analyzed systematically, the manual interpretation process requires sampling and frequent judgment calls, both of which introduce inaccuracy.
- Frequency: Presently, the time and expense of aerial photo collection and interpretation limit the extent and update frequency of SPB hazard maps. If the process were relatively inexpensive and automated, hazard maps could be generated frequently over larger areas.

To address these limitations, the Texas Forest Service (TFS) and Forest One (now Lanworth, Inc.), with the support of the USDA Forest Service Southern Research Station, began a project to investigate the potential of satellite imagery and digital image processing methods to lower the costs and improve the accuracy of the operational east Texas SPB hazard maps. Here we report the principal results of this investigation in a pilot area of east Texas (Figure 1), specifically:

1. Development and integration of satellite and digital inputs into the Billings and Bryant model.
2. Accuracy assessment of the model inputs.
3. Validation of the model adaptation through comparison of satellite-derived SPB hazard maps to operational maps produced by TFS.
4. Revalidation of the model through comparison satellite-derived SPB hazard maps to known locations of SPB infestation.

Methodology

The Billings and Bryant model of SPB hazard takes the form of the discriminant function:

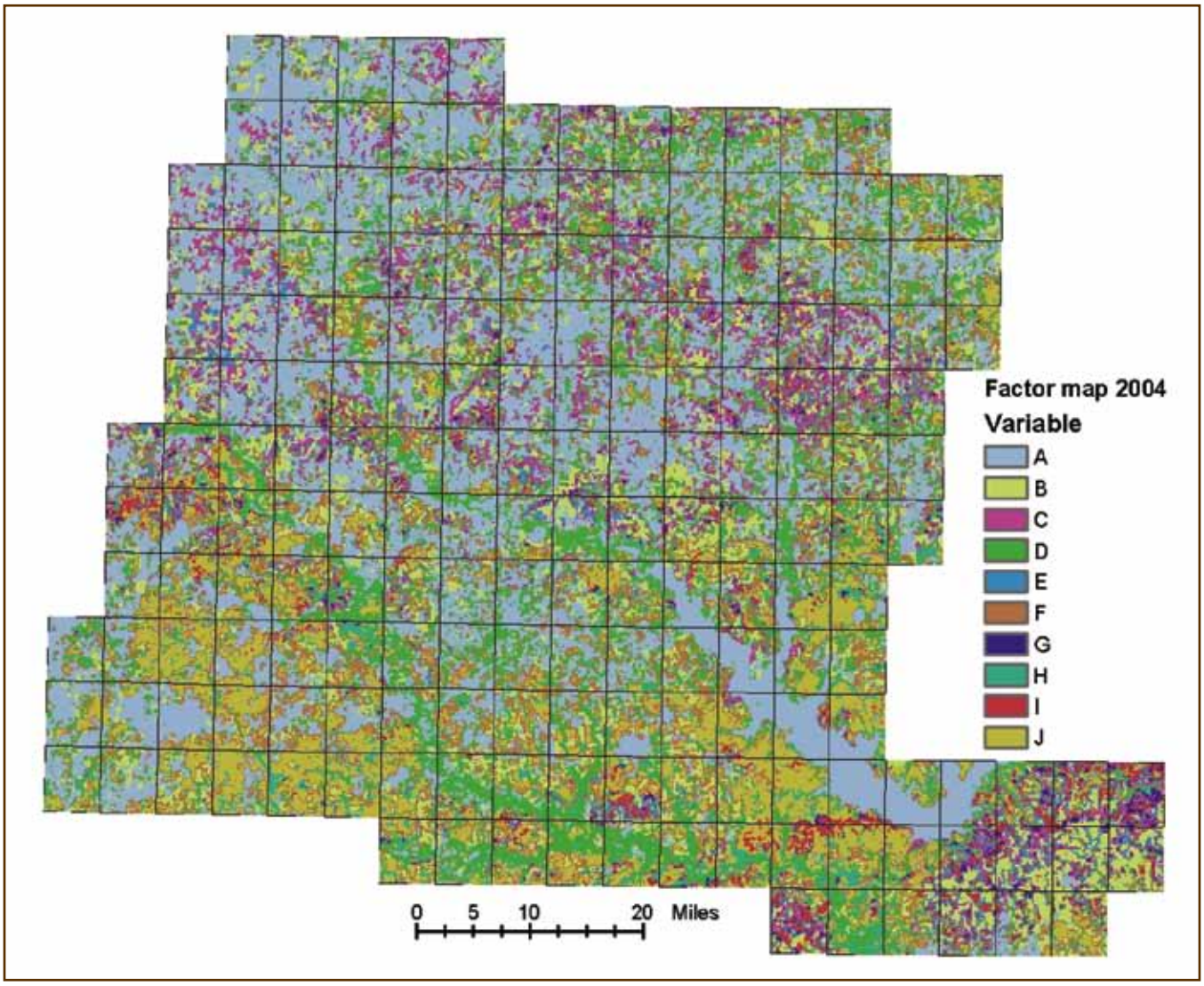

Figure 2—Distribution of hazard factor combinations (habitat types) across the project area (December 2004).

$$DS = -1.35 - 0.108(A) + 0.135(D) + 0.330(E) + 0.404(F) + 0.305(I) + 0.271(J)$$

where the values of the discriminating variables A, D, E, F, I, and J are the numbers of photo plots in a grid block that have the combination of site/stand factors listed in Table 1. Thus, if five photo plots in a given grid block fall on water or agricultural land (factor combination A) and seven others fall on dense, old pine (factor combination I), the values of variables A and I are 5 and 7, respectively. Because only 20 photo plots are analyzed per grid block, the possible value of each variable ranges from 0 to 20. Note, however, that the values of the discriminating variables will not necessarily sum to 20 as not all site/stand factor combinations appear in the discriminant function.

The challenge of applying satellite data to the determination of SPB hazard at the grid block scale lies in replicating the process of photo interpretation used by TFS without violating the assumptions and conditions of the discriminant function.

The foundation of our approach to SPB hazard mapping is Forest One's Forest Age Map product, a raster map based in Landsat imagery in which each 28-m (30.6 yd) cell (pixel) is classified into one of four forest types (softwood, hardwood, mixed, nonforest) and in which all softwood

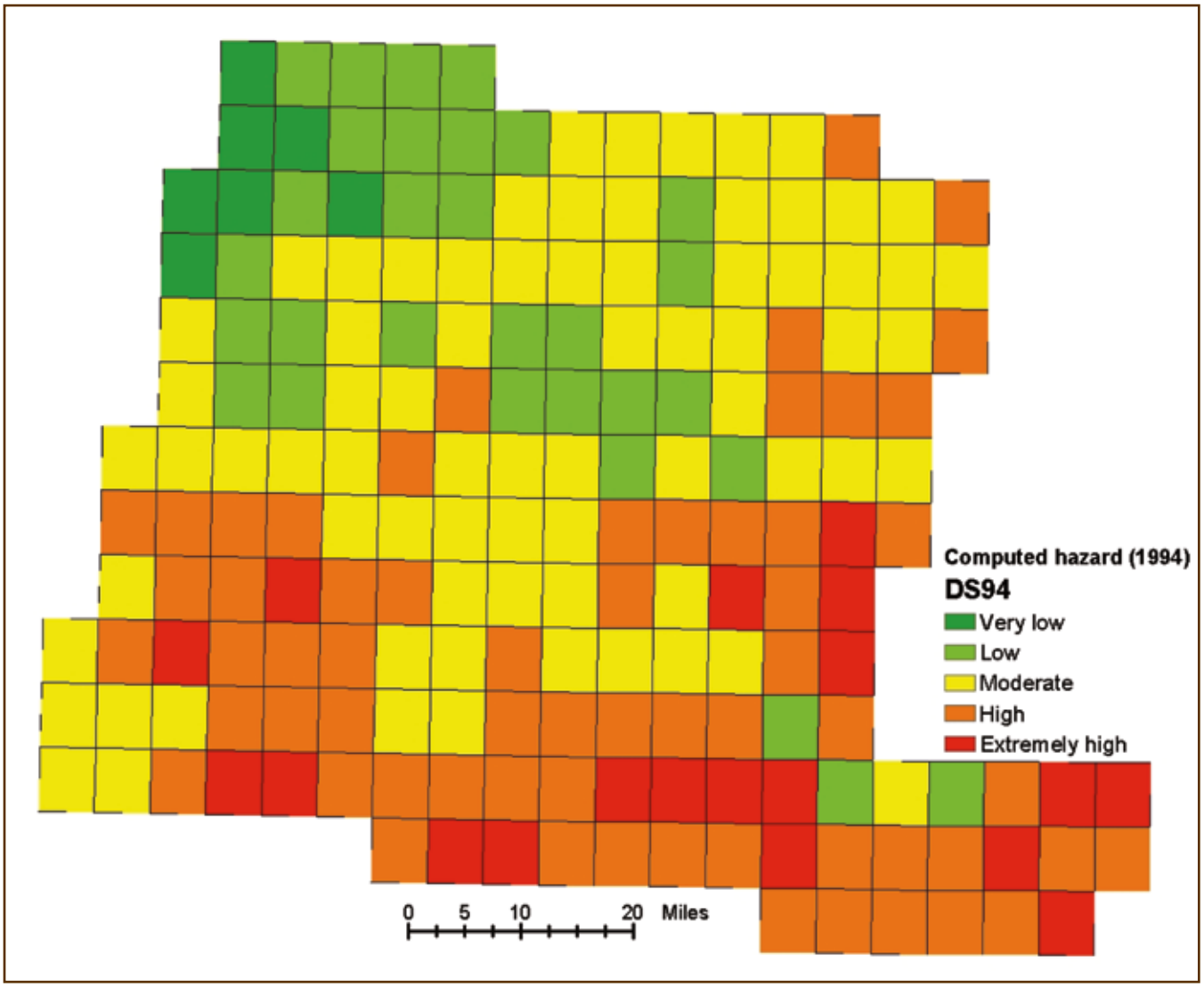

Figure 3—Grid block hazard ratings for 1994 derived from satellite and digital geospatial data.

pixels are further classified into 3-year age classes (e.g., 0 to 3 years, 7 to 10 years, etc.). To develop a SPB host map for the year 2004, Forest One recoded its Forest Age Map, classifying all hardwood, nonforest, and softwood younger than 15 years as nonhost and all softwood older than 15 years as host. To compare satellite-derived SPB hazard to existing TFS hazard maps from 1996 and SPB spot data from 1989 to 1993, Forest One also prepared Forest Age Maps and host maps for 1994 and 1990.

Because the TFS hazard rating protocol considers the percentage of host pine within a 30-acre (12.1 ha) photo plot rather than the predominant host type in a 28-m (30.6 yd) (12.1 ha) pixel, the host maps must be transformed to represent varying percentage of host pine across the study area. This was accomplished by recoding the host maps so that pixels classified as nonhost and young pine have a value of 0, and pixels classified as pine host have a value of 1. A 13 x 13 average filter was then passed over the recoded maps, replacing each pixel by the arithmetic mean of its neighborhood. A 13 x 13 matrix of 28-m (30.6 yd) pixels has an effective area of 32.7 acres (13.2 ha), and the resulting pixel value will therefore estimate the proportion of host pine in a photo plot-sized area centered on each pixel.

Table 2—Comparison of satellite (Forest One 1994) and photo-interpreted (TFS 1996) hazard class predictions. Agreement within 1 hazard class is 89 percent

Texas Forest Service **hazard class**	**F1 hazard class**					
	Extreme	High	Moderate	Low	Very low	Total
Extreme	4	1	0	4	0	5
High	5	11	9	5	0	30
Moderate	5	13	16	27	5	66
Low	1	5	13	41	21	81
Very low	0	0	0	7	1	8
Total	15	30	38	80	27	190

	N	**Percent**
Agreement	73	38 percent
F1 underestimate (1 class)	58	31 percent
F1 overestimate (1 class)	38	20 percent
Disagreement	21	11 percent

As a further qualification of site/stand conditions, the TFS hazard rating protocol measures host density as a function of canopy closure in areas of each plot containing host pine. As a proxy for host density, we selected a vegetation index computed from the red, near-infrared, and midinfrared bands of Landsat TM imagery acquired in 1990, 1996, and 2004. The vegetation index, called NDVIc, uses the distinctively high reflectance of green vegetation in the near-infrared wavelengths relative to the red and middle-infrared wavelengths to map the relative distribution of green biomass across the project area. Furthermore, because soils tend to reflect strongly in the middle-infrared wavelengths, middle-infrared reflectance is negatively correlated with canopy closure. NDVIc is a unitless quantity that varies between -1 and 1. To restrict this measurement to areas of host pine, the host maps were used to assign null values to areas of young pine and nonhost. A 13 x 13 average filter was then passed over the NDVIc maps to estimate for each pixel the average density of host pine in a photo plot-sized area centered on that pixel.

Current TFS protocol distinguishes between pine stands with less than 80 percent canopy closure and those with 80 percentage of closure or greater. To determine the actual relationship between NDVIc and percentage of canopy closure, we partitioned several 1-m color-infrared digital orthophoto quarter quadrangles from 1995 into canopy and noncanopy pixels. We then computed the proportion of 1-m (39.4 in) canopy pixels present within the area covered by each 28-m (30.6 yd) pixel from a 1994 Landsat image. The average NDVIc value of all Landsat pixels containing more than 80 percent crown elements (NDVIc = 0.425) was then selected as the threshold for 80 percent canopy closure.

The final site/stand factor considered under the TFS protocol is landform, expressed as bottomland or other terrain. To determine the landform most characteristic of the photo plot-sized area centered on each 28-m pixel within the

Table 3—Observed rates of SPB[a] infestation (1991-93) by satellite-predicted hazard class (1990)

Hazard class	New spots (1991-93)	N Grid blocks	Infestation rate (spots/class/ grid block)
Extreme	159	15	10.60
High	409	28	14.61
Moderate	652	58	11.24
Low	583	81	7.20
Very low	21	8	2.63

[a] SPB = Southern pine beetle.

study area, the National Elevation Data set digital terrain model was resampled to match the grid resolution of the Forest Age Map. Percentage of slope was then computed for each grid cell, and a 13 x 13 average filter was passed over both the slope and elevation maps. Based on conversations with photo interpreters at TFS, bottomland was operationally defined as those areas having an average elevation less than 90 m (98.4 yd) and an average slope less than 3 percent.

Once all relevant site/site-stand factors were estimated using remotely sensed inputs, a series of rules was used to assign each pixel to 1 of the 10 factor combinations expected by the Billings and Bryant model (Figure 2). Once a site/stand factor combination was assigned to each 28-m grid cell, the percentage coverage of each factor combination was computed for each of the 190 grid blocks in the study area. This percentage value was then multiplied by 0.2 to scale percentage cover to the 0 to 20 range expected by the discriminant function. The discriminant score was then computed for each grid block for the years 1990, 1994, and 2004, and scores were assigned to hazard classes based on breakpoints used in the 2003-04 TFS update. The satellite-derived hazard map for 1994 is shown as Figure 3.

Accuracy of Model Inputs

To determine the accuracy of the satellite-derived inputs, we compared our maps of host type and coverage to reference data on managed pine stands of known age. The reference data were distributed widely across the project area and constitute a 5-percent sample by area. Analysis shows that Forest One's Forest Age Map classifies pine with at least 80 percent accuracy and can distinguish between pine greater than 15 years and pine younger than 15 years with 82 percent accuracy. We also compared our measurements of crown closure and landform to operational photo-interpreted measurements made by TFS technicians and found similar levels of agreement. Our conclusion, therefore, is that the satellite-derived inputs into the model are sound.

Comparison of Satellite-Derived and TFS Hazard Maps

The principal result of our work so far has been SPB hazard maps for 1990, 1994, and 2004. The accuracy of the 2004 map is currently being assessed through comparison to operational measurements of hazard factors by TFS. The accuracy of the 1994 map has been assessed through comparison to the 1996 hazard map produced by TFS (Table 2).

The comparison shows that the 1994 map correctly predicted the hazard rating of 38 percent of the grid blocks. The maps predicted a further 51 percent of the grid blocks within 1 hazard rating class. Given some uncertainty about the accuracy of the TFS reference map, we propose to treat all agreements within 1 hazard class as correct predictions and offer 89 percent as the final accuracy of the satellite-derived hazard map. In general, the satellite-derived map tends to underpredict hazard ratings slightly. Forest One and TFS are working to explain and improve the correspondence between the two hazard rating systems.

Comparison of Satellite-Derived Maps and Historic SPB Infestation Data

As a further check on the accuracy of the satellite-derived hazard map and the validity of the underlying discriminant function, TFS supplied data on the location of SPB infestations within the study area during the years 1989-93. These data were organized as SPB infestation counts for each 15-arc second grid block within the study area. To compare these data to the 1990 satellite-derived hazard map, we selected all 15-arc second grid blocks that were infested in 1991, 1992, or 1993 but not in 1989 or 1990. This allowed us to create a map of new infestations since 1990. These infestations were presumably related to landscape conditions

represented by the 1990 satellite map rather than to lingering or renewed infestations from prior years.

To allow comparison of new infestations to satellite-predicted hazard class in 1990, we aggregated all new infestations to the 18,000-acre grid block level and summarized these counts by hazard class (Table 3). Because the area (number of grid blocks) of each hazard class is not constant over the study area, we divided the count of new infestations by the number of grid blocks in each hazard class that were either newly infested in 1991-93 or were not infested at all. This normalized measure was interpreted as the average infestation rate for each hazard class.

Our results reveal a qualitatively strong, positive correlation between the observed infestation rate and the model -predicted hazard class. The mean rate of SPB infestation declined from nearly 15 infestations/grid block in the high hazard class to fewer than 3 infestations per grid block in the very low hazard class. The only observed anomaly is that the infestation rate is slightly lower than expected for the extreme hazard class, perhaps indicating limited resolving power of either the satellite data or the underlying model. This anomaly is currently being investigated by Forest One and TFS.

Conclusions

From the investigations and analyses reported here, we conclude that satellite imagery, together with ancillary digital geospatial data and automated processing techniques, presents a powerful and cost-effective tool for operational mapping of SPB infestation hazard at the landscape scale.

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Previsual Detection of Two Conifer-Infesting Adelgid Species in North American Forests

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Abstract

The balsam woolly adelgid, *Adelges piceae*, and hemlock woolly adelgid, *A. tsugae* (Homoptera: Adelgidae), are invasive pests of coniferous forests in both the Eastern and Western United States. Balsam woolly adelgid is capable of attacking and killing native North American firs, with Fraser fir (*Abies fraseri* (Pursh) Poir.) in the East and subalpine fir (*A. lasiocarpa* (Hook.) Nutt.) in the West being particularly susceptible to infestation. Hemlock woolly adelgid is capable of infesting native hemlocks and is a serious pest in forests of the Eastern United States where it is causing significant mortality to both eastern (*Tsuga canadensis* (L.) Carr.) and Carolina hemlock (*T. caroliniana* Engelm.). Infestations by either of these insects may take several years to kill the host tree. Damage by hemlock woolly adelgid frequently causes needles to discolor from deep green to grayish green. Discoloration of needles is also one of the symptoms used to diagnose infestations of balsam woolly adelgid. Traditional methods for assessing damage by these adelgid species include field surveys and aerial detection surveys. However, because infestations frequently occur in remote locations and can take years to build up, stand damage may accrue prior to visual detection of the infestations. Branch-level, spectral data of the foliage from trees were collected for several categories of infestation. In the Western United States, data were collected from subalpine fir infested with balsam woolly adelgid in northern Idaho. In the Eastern United States, data were collected from eastern hemlock in western North Carolina. Trees were sampled using a hand-held spectroradiometer. The measured radiance spectra were converted to percentage of reflectance and comparisons made between the infestation categories. Separation of the infestation levels occurred in a progressive pattern moving from noninfested to newly (or lightly) infested to heavily infested trees. Results suggest that previsual detection of this group of invasive insects may be possible with appropriate spatial and spectral sensor resolution.

Keywords: Host resistance, hyperspectral, insect detection, multispectral, remote sensing.

Invasive Adelgids in North American Conifers

Adelgids (Homoptera: Adelgidae) are small insects with piercing and sucking mouth parts. They have a white woolly covering that is secreted over the body. There are several native adelgid species within North America such as the Cooley spruce gall adelgid (*Adelges cooleyi*), and some of these can cause growth loss in trees or cause trees to reach economic injury levels under some conditions. However, the two adelgid species that are currently causing the most economic and ecological impacts within North America are the introduced balsam woolly adelgid (*A. piceae*) and the hemlock woolly adelgid (*A. tsugae*), both of which are established in both the Eastern and Western United States.

Balsam Woolly Adelgid: Hosts and Biology

Balsam woolly adelgid is native to the fir forests of central Europe and was introduced into the United States around 1900. The life cycle of the balsam woolly adelgid consists of the egg, three larval instars, and the adult (see Hain 1988 for a more thorough description). The only life stage capable of movement is the first instar larva (termed the crawler) that, upon locating a suitable feeding site, inserts its stylet into the bark and transforms (without molting) into a nonmobile phase, after which the insect is permanently attached to the host tree. As the female feeds, she secretes a dense woolly covering that ultimately covers the entire insect.

The crawler stage does not have wings, and between-tree dispersal is a passive process. The adult female produces as many as 248 eggs. These are oviposited within the woolly mass, which acts to protect all of the life stages except the crawler.

All of the true firs (*Abies*) that are native to North America show some degree of susceptibility to the balsam woolly adelgid (Mitchell 1966). The susceptibility ranges from slight for noble fir (*A. procera* Rehd.) and white fir (*A. concolor* (Gord. & Glend.) Lindl. ex Hildebr) to moderate for grand fir (*A. grandis* Dougl. ex D. Don) Lindl., corkbark fir (*A. lasiocarpa* var. *arizonica* (Merriam) Lemm.), and Shasta red fir (*A. magnifica* var. *shastensis* Lemm.) to severe for subalpine fir (*A. lasiocarpa* (Hook.) Nutt.), Fraser fir (*A. fraseri* (Pursh) Poir.), balsam fir (*A. balsamea* (L.) Mill.), and Pacific silver fir (*A. amabilis* Dougl. ex Forbes). The insect is established on susceptible hosts in the Eastern and Western United States where it is responsible for significant levels of mortality in some stands. Prior studies suggest that there may be some connection between host monoterpenes and attack success by balsam woolly adelgid (Arthur and Hain 1987).

Hemlock Woolly Adelgid: Hosts and Biology

Hemlock woolly adelgid is native to Asia and was first reported in the Pacific Northwest in the 1920s. The adelgid was reported in Eastern North America in the 1950s and Connecticut in the 1980s. The insect is now present in many of the hemlock forests of the Eastern United States, where infestations frequently result in significant mortality to native hemlocks (Souto and others 1995). The hemlock woolly adelgid is a serious pest of Eastern hemlocks and represents a significant threat to the sustainability of native hemlocks (*Tsuga canadensis* (L.) Carr. and *T. caroliniana* Engelm) in the Eastern United States (McClure 1992). Whereas the adelgid is also established in the Western States, it does not appear to be a threat to the western hemlock species (*T. heterophylla* (Raf.) Sarg. and *T. mertensiana* (Bong.) Carr.) at the present time.

Hemlock woolly adelgid has two generations per year in much of its range in the Eastern United States. Only females are present, and the spring generation lays between 100 and 300 eggs. Upon hatching, the crawlers search for suitable feeding sites, insert their stylets and begin to feed. As with balsam woolly adelgid, crawlers become immobile once they settle and begin to feed. When the crawlers reach maturity, two types of adults can form. One type of adult has wings and dies as it searches for the alternate spruce host, which is not present in North America. The other is wingless and capable of laying eggs to produce the next generation.

Conifer Resistance to Insect Attack

There are several hypotheses regarding plant resistance to insect attack that involve the production and allocation of resources within the plant as they relate to the plant's resistance mechanisms. The carbon: nutrient balance hypothesis correlates the production of plant secondary metabolites that are important in determining the relative resistance/susceptibility of the plant with the ratio of carbon to other nutrients within the plant (see Herms and Mattson 1992). The growth differentiation balance hypothesis also views changes in the production and maintenance of plant secondary metabolites as a tradeoff owing to environmental constraints on growth and secondary metabolism (i.e., differentiation) (see Herms and Mattson 1992). The growth differentiation balance hypothesis predicts that under moderate stress, plant growth will be limited, and the production of secondary metabolites such as those important in insect resistance will increase.

Conifer Resistance to Insect Attack: Generalized Response Sequence

Conifer resistance to stem-invading insects has received much attention and involves a generalized, three-step sequence of wound cleansing, infection containment, and wound healing (Berryman 1972, Hain and others 1983). The first step of this response, wound cleansing, is characterized by the production and flow of constitutive resins. The second step of the resistance sequence, infection containment, can be described as a rapid necrosis of cells surrounding the infection site that is accompanied by the development of traumatic resin ducts and an increased concentration of monoterpenes and phenolics in the reaction zone (Cook

and Hain 1986, Raffa and Berryman 1982, Reid and others 1967). The accumulation of terpenes and phenolics in the reaction zone is also accompanied by a decrease in the level of soluble sugars in that zone (Cook and Hain 1986, Wong and Berryman 1977). Wound healing, or formation of wound periderm, is the final step of the resistance sequence. This isolates the wound from the rest of the tree. Wound periderm is located adjacent to the necrotic tissue and protects living tissue from the adverse effects of the dead cells in the necrotic zone surrounding the attack site(s) (Mullick 1977). The three-step resistance sequence requires an expenditure of energy by the tree, and there is typically a resulting change of color (fading) within the tree's foliage.

Fir Response to Stem Attack by the Balsam Woolly Adelgid—

The impact of balsam woolly adelgid infestation on North American firs has been studied extensively over the past several decades. Infestation by the adelgid results in anatomical and structural changes within host tissues that may be the result of salivary excretions from the insect's stylet during feeding. Physically, the xylem tissue of infested trees has higher concentrations of ray tissue (Mitchell 1967, Smith 1967), thickened cell walls, and shorter tracheids (Doerksen and Mitchell 1965). The tracheids have encrusted pit membranes that more closely resemble the pit membranes associated with heartwood (Puritch and Johnson 1971). There is a corresponding reduction in waterflow in infested trees (Mitchell 1967) that puts the tree into a state of physiological drought; this, in turn, reduces photosynthesis and respiration (Puritch 1973) and can ultimately result in tree death.

The damage to the host tree is related to both the size of the tree and the intensity of the infestation. Balsam woolly adelgid infestations in the crown of a tree usually result in gouting of the outer branches (characterized by node or bud swelling or both with a decrease in new growth of the stem and foliage) (Mitchell 1966). Over time, the crown thins, and the foliage fades in color. Balsam woolly adelgid infestations also occur on the stems of trees. In North America, these stem infestations usually kill native firs within 6 years (Hain 1988).

Hemlock Resistance to Attack by Hemlock Woolly Adelgid—

Once hemlock woolly adelgid settles onto a twig, the tree usually suffers needle loss and bud mortality, followed by branch and whole tree mortality (usually within 6 years) (McClure 1991, Shields and others 1995). Foliar chemistry appears to play some role in host susceptibility/resistance to hemlock woolly adelgid, with resistance being related to foliar levels of calcium, potassium (K), nitrogen (N), and phosphorous (Pontius and others, 2006). These authors suggest that higher levels of N and K in the foliage enhance host palatability and, thus, result in increases in the population levels of hemlock woolly adelgid. In addition, soil and foliar chemistry along with landscape position can be used to model hemlock susceptibility to Hemlock Woolly Adelgid (Pontius and others 2009). These hypothesized relationships between foliar chemistry and infestation could be important for early detection of hemlock woolly adelgid infestations because some foliar constituents such as chlorophyll, N, cellulose, and sugar can be accurately estimated using spectral data (Curran and others 2001).

As with other conifers, monoterpenes are major constituents of tree chemistry of hemlocks (i.e., Li and others 2001). These compounds may function in several ways to mediate the interaction between trees and herbivores, but one impact is that they are frequently toxic to attacking insects such as bark beetles (i.e., Cook and Hain 1988) or other arthropods such as spider mites (i.e., Cook 1992). It has been suggested that the monoterpene content of western hemlocks may function as a deterrent to hemlock woolly adelgid (Lagalante and Montgomery 2003). The authors suggest that elevated levels α-pinene, β-caryophyllene, and α-humulene may act as feeding deterrents against hemlock woolly adelgid, and that elevated levels of isobornyl acetate may attract the adelgid.

Importance of Previsual Detection

Minimizing the elapsed time between when a tree becomes infested with an insect and when that infestation is detected can increase the treatment options available to forest managers. Detection of an infestation prior to when the foliage begins to visibly fade should give managers more

time to respond. Active resistance mechanisms by a host tree to insect attack can be energy intensive to maintain and utilize. The decline that occurs within a host following infestation by adelgids may be categorized into various levels as characterized for hemlock infested with hemlock woolly adelgid (Pontius and others 2005) or balsam fir infested with balsam woolly adelgid (Luther and Carroll 1999). Changes in foliar chemistry that are related to tree stress can be manifested in measurable spectral changes within the foliage. Much of the literature with regard to another tree-killing insect, mountain pine beetle (*Dendroctonus ponderosae*), is reviewed by Wulder and others (2006). The review suggests that remotely sensed data is useful for detecting infestations of mountain pine beetle damage and that future experimental work be conducted at several spatial scales.

Spectral Data

Both the spatial resolution (i.e., pixel size) and spectral resolution (the width of the individual spectral wavebands over which plant response is measured) of spectral data, as well as the overall wavelength range examined (some sensors operate through the middle infrared region, some do not), can influence the ability to detect infested trees. Multispectral remotely sensed data types tend to have fewer, wider spectral wavebands and are operationally available from satellite platforms over a wide range of spatial resolution (< 1 to 30 m). Landscape-scale hyperspectral data are less widely available and have a large number of very narrow wavebands. Because most available data sets are acquired from aircraft platforms, these data tend to have spatial resolution on the order of 6 to 20 m. Handheld spectroradiometers with wavelength widths and numbers similar to hyperspectral sensors are often employed in the field and laboratory to study spectral response of canopy components.

Prior Attempts to Use Spectral Imagery to Detect or Delineate Adelgid Infestations

There have been several prior studies related to the detection and classification of trees infested with invasive adelgids. Luther and Carroll (1999) examined several foliar indices for assessing stress in balsam fir using spectral reflectance data and reported that foliar reflectance decreased consistently with vigor. These authors conducted their work in the laboratory using a fixed-position spectoradiometer. Adelgid infestation was not specifically investigated, but infestation of fir with balsam woolly adelgid does result in tree stress (see Hain 1988). At the landscape scale, hemlock stands were similarly assessed and analyzed for health status using multispectral Landsat Thematic Mapper data (Bonneau and others 1999). The best overall accuracy for classifying stand health based on hemlock woolly adelgid infestation was obtained using the Modified Soil Adjusted Vegetation Index-2. Pontius and others (2005) used hyperspectral data to examine the abundance and early decline of hemlock infested with hemlock woolly adelgid. These authors suggest that wavelengths in the low end of the spectral range may be useful in assessing early stages of decline of hemlock infested with hemlock woolly adelgid. One purpose of our ongoing research is to determine if host decline resulting from infestation by invasive adelgids in multiple tree genera can be evaluated by using similar spectra among the host genera.

Comparison of Hyperspectral Data for the Previsual Detection of Balsam Woolly Adelgid and Hemlock Woolly Adelgid Infestations

Our studies have used hyperspectral data collected at the branch level. Spectral data were collected using a Geophysical Environmental Research Corp. 2600 handheld spectroradiometer with a spectral resolution of 1.5 nm from 350 nm to 1050 nm and a resolution of 11.5 nm from 1050 nm to 2500 nm. In the case of balsam woolly adelgid, we have concentrated on subalpine fir, the primary host of this insect in Idaho. Our studies of hemlock woolly adelgid have concentrated on its primary host in western North Carolina, *Tsuga canadensis*. For both insect-tree pairs, spectral data were collected from trees in various stages of infestation. Five branches were cut from each tree that was examined. Branches were cut from various heights and orientations throughout the canopy of the trees. The branches and foliage were placed on a flat black surface with negligible amounts of measurable radiation, and five measurements per tree

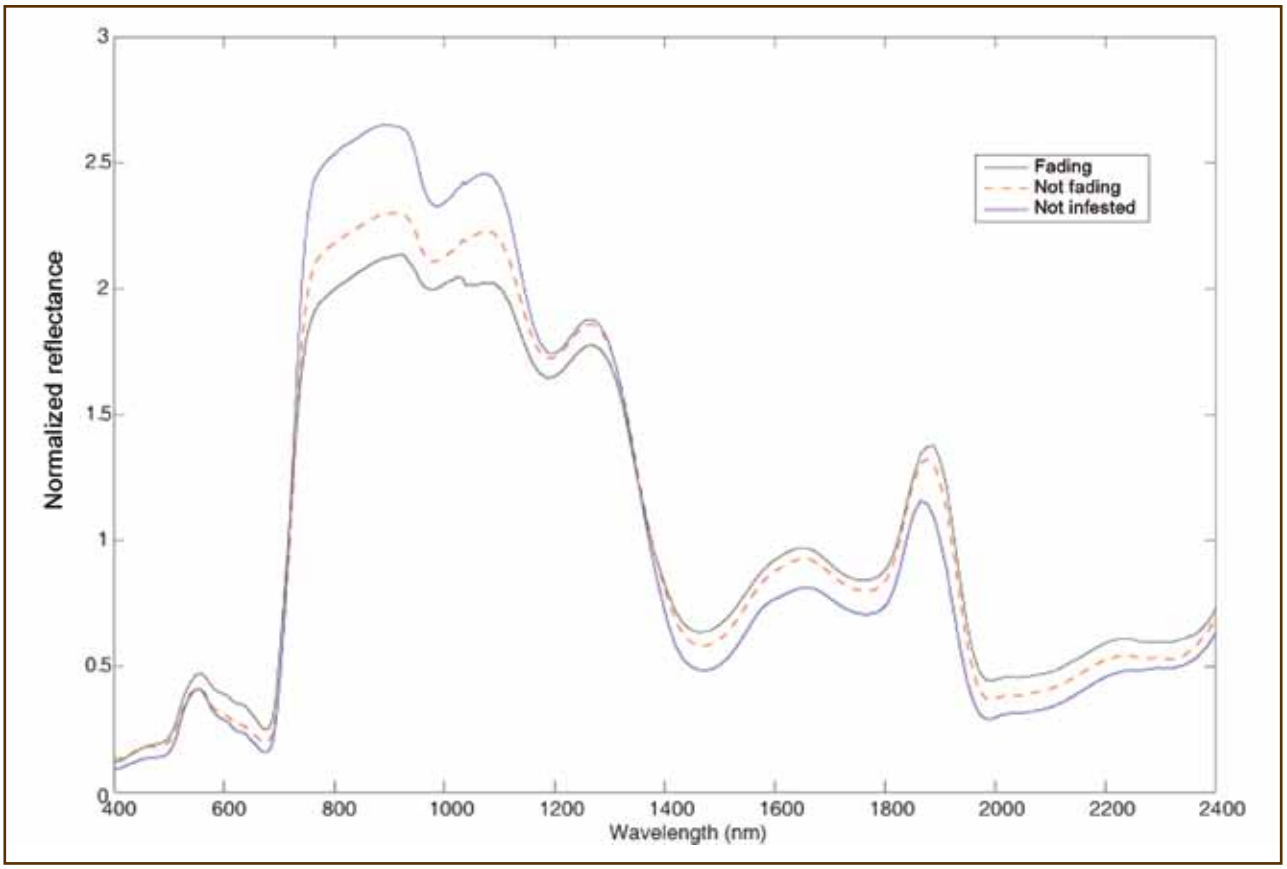

Figure 1—Spectral measurements of subalpine firs, *Abies lasiocarpa*, in Idaho with three levels of infestation with balsam woolly adelgid, *Adelges piceae*. The infestation categories are not infested = blue, infested but with no visible symptoms = red, and infested with visible symptoms = black.

were obtained in an iterative manner, with the foliage being rearranged between each measurement. The radiometer was placed at a height of approximately 50 cm above the branch samples, and measurements were made when the sun angle was within 10° of solar noon. The spectra for these five replicates of branch measurements were averaged to obtain a measure of each tree's reflectance properties. The data for each tree were smoothed using a weighted moving filter, and comparisons were made of the spectral response among infestation classes.

In Idaho, subalpine firs in three infestation categories were sampled. The categories included trees that had no current infestation with balsam woolly adelgid, trees that were infested with balsam woolly adelgid but had no apparent crown fading, and trees that were infested with balsam woolly adelgid and had visible signs of this infestation. Using Analysis of Variance procedures and the SAS statistical analysis package, significant differences were found among the three infestation categories for some wavelength regions. Our results demonstrated a consistent response in the normalized spectral reflectance curve of subalpine fir, stressed by infestation of balsam woolly adelaid, across the reflectance spectrum shown in Figure 1. More specifically, there is an increased reflectance in the visible region of the reflectance curve (< 700 nm), decreased reflectance in the Near Infra Red plateau (centered around 1000 nm), and increased reflectance in the shortwave infrared region (beginning around 1450 nm) as visual decline becomes apparent. The overall changes in spectra are similar to those reported for other stresses in balsam fir (Luther and Carroll 1999). Multispectral aerial imagery (Landsat and SPOT data) was also collected for areas with active balsam woolly adelaid infestations. Because of the relatively

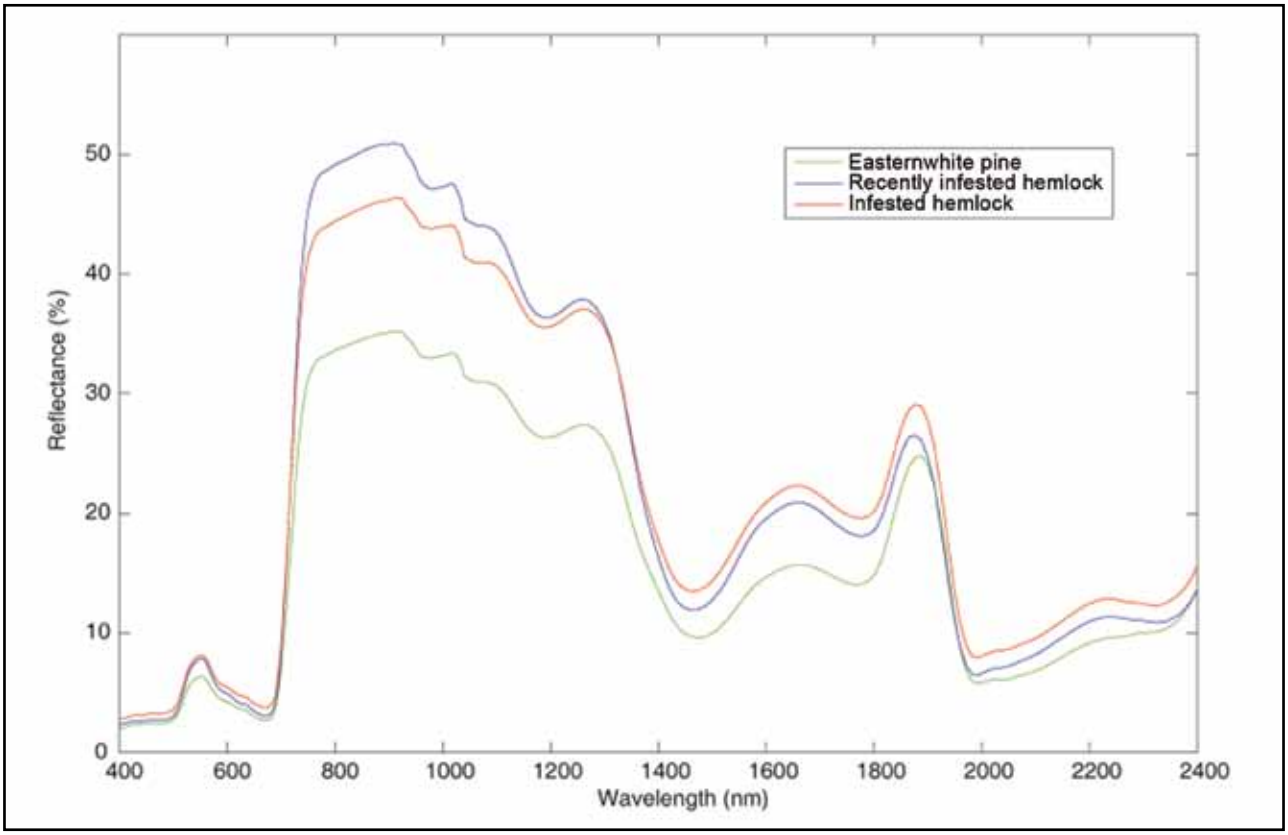

Figure 2—Spectral measurements of eastern white pine, *Pinus strobus*, and eastern hemlocks, *Tsuga canadensis*, in North Carolina with two levels of infestation with hemlock woolly adelgid, *Adelges tsugae*. The spectral categories are eastern white pine = green, recently infested but with no visible symptoms = blue, and infested with visible symptoms = red.

narrow canopy architecture of subalpine fir and the patchy distribution of the species in the areas of data collection, no conclusive results were obtained.

In North Carolina, hemlock trees that were recently infested (within the past year) or that had been infested for multiple years were sampled as was eastern white pine (*Pinus strobus* L.) (the only other conifer present within the stands that we sampled) during June of 2005. No uninfested stands of hemlock were found within the study areas. There were visible differences in the overall spectral measurements between the hemlocks that were recently infested with hemlock woolly adelgid and those that had been infested for a longer period of time (Figure 2). The spectral signature of eastern white pine, the only other conifer present within the stands that could be confused with the hemlocks, differed significantly from both categories of infested hemlock within the stands (Figure 2). The pattern of decreased spectral values with increasing stress is similar to the decreases measured in subalpine fir infested with balsam woolly adelgid in the Near Infa Red plateau and increases again in the shortwave Infa Red region (Figure 1). The ability to distinguish declining hemlock at the branch level also supports the prior landscape-level investigations of Pontius and others (2005), but larger data sets from a variety of geographic locations are still needed.

Implications for Detection and Delineation of Forest Insect Infestations

The branch-level spectral data for both tree species infested with their specific invasive adelgids were both consistent and in general agreement with the shoot-level spectral changes of balsam fir under various stresses that were measured under laboratory conditions (Luther and Carroll 1999). The measurements were also in general agreement with the results of Pontius and others (2005) who examined

hemlock woolly adelgid at the landscape level. Therefore, the spectral changes that occur with stress are measurable at several scales. The combined results of these studies suggest that spectral data may aide in developing a tool for previsual detection and monitoring of forest decline associated with these adelgid species. However, limitations do exist. One of the primary limitations may be the ability to separate different stressing agents or factors.

Acknowledgments

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Estimating the Susceptibility to *Phytophthora alni* Globally Using Both Statistical Analyses and Expert Knowledge

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Abstract

Phytophthora alni subspecies *alni* Brasier and S.A. Kirk is a recently hybridized soil and waterborne pathogen causing root and collar rot of species of the genus *Alnus* spp. (alder). It has quickly spread throughout Europe via planting of infested nursery stock and irrigating fields with infested river water. Once introduced, the pathogen spreads naturally by means of streams, floods, and other drainage water. *Phytophthora alni* can also be passively transported with the bare-root nursery stock, as it is able to adhere to and infect fine roots of visually symptomless plants of alder and other tree species exposed to the pathogen.

We used a classification tree on 434 infested and healthy sample points to determine the required conditions for *P. alni* to successfully infest a nonflooded forest site. Sample points had been collected from 2003 through 2006, and a potential distribution surface was created for forested areas in Bavaria. A tenfold cross-validation accuracy of 78 percent was attained. To understand the potential hazard posed by *P. alni* elsewhere in the world, the rules from the Bavarian classification tree were applied along with additional expert knowledge in a multicriteria model to create a global susceptibility surface for *P. alni*.

Keywords: Alder, *Alnus*, classification tree, hazard, pathogen, *Phytophthora alni*, risk.

Introduction

Phytophthora alni Brasier and S.A. Kirk is a host-specific, highly aggressive soil and waterborne pathogen that causes root and collar rot of *Alnus* (alder) spp. All European alder species (i.e., black alder [*A. glutinosa* (L.) Gaertn.], gray alder [*A. incana* (L.) Moench], Italian alder [*A. cordata* (Loisel.) Duby], and green alder [*A. viridis*] (Chaix) DC.) and the North American red alder (*A. rubra* Bong.) are highly susceptible (Jung and Blaschke 2006, Gibbs and others 2003). The susceptibility of other North and South American and Asian alder species is currently unknown. *Phytophthora alni* was shown to be a recent interspecific hybrid between *P. cambivora* (Petri) Buisman and another species closely related to *P. fragariae* Hickman (Brasier and others 1995, 1999, 2004). There are three subspecies of *Phytophthora alni*, with markedly different aggressiveness to common alder (Brasier and others 2004, Brasier and Kirk 2001). The disease was first detected in 1993 in Southern Britain (Gibbs 1995) and has since been confirmed in 12 other European countries and across the United Kingdom (Figure 1) (Brasier and Jung 2003, 2006; Gibbs and others 1999, 2003; Jung and Blaschke 2004, 2006; Schumacher and others 2005; Streito and others 2002) (Orlikowski, L. Pers. comm., 2006. Pathologist, Research Institute of Pomology and Floriculture, Pomologiczna 18, 96-100 Skierniewice, Poland). Moreover, *P. alni* is likely present in Czech Republic, Spain, and Switzerland because typical symptoms and mortality of alders are reported from these countries. The disease occurs mainly along riverbanks, but also in orchard shelterbelts and forest plantations (Gibbs 1995; Gibbs and others 1999, 2003; Jung and Blaschke 2004; Streito and others 2002). Disease symptoms include abnormally small, sparse, and often yellowish foliage and crown dieback (Figure 2). Other symptoms are early and often excessive fructification and tongue-shaped necroses of the inner bark and cambium. Necroses can extend up to 3 m from the stem base and are marked by tarry or rusty spots on the surface of the outer bark (Figure 3) (Gibbs and

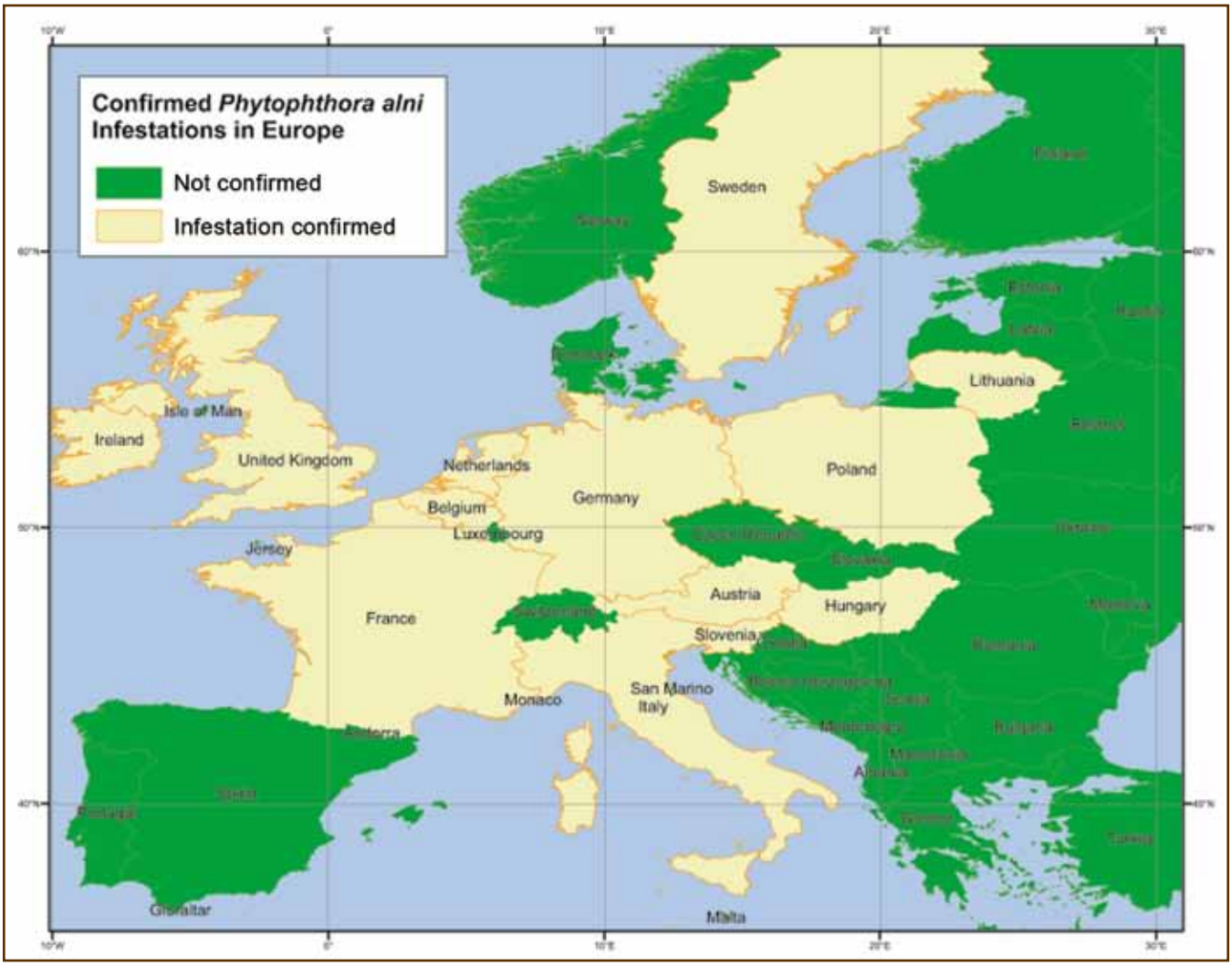

Figure 1—Current distribution of *Phytophthora alni* (yellow).

others 1999, 2003; Jung and Blaschke 2001, 2004) (http://www.baumkrankheiten.com/gallery/docs-en/alder_dieback/index.html). On riparian sites, *P. alni* has caused mortality as high as 70 percent in some locations. Disease incidences of 50 percent and high mortality rates were common (Gibbs and others 2003, Jung and Blaschke 2004, Streito and others 2002). The pathogen was shown to be widespread in alder nursery fields (Jung and Blaschke 2004, Schumacher and others 2005). Infected plants seldom showed symptoms, which made control efforts difficult.

A thorough investigation of disease pathways in Bavaria demonstrated that in most infested river systems, *P. alni* was introduced via infested young alder plantations established on the riverbanks or on forest sites that drain into the rivers (Jung and Blaschke 2004). Once introduced, *P. alni* spreads downhill with water runoff and downstream with streams and floods. Many infected alders were planted in afforestations of former agricultural land and also on wet sites in woodlands to stabilize steep slopes and banks of white water rivers (Jung and Blaschke 2004). These plantings increased the risk of infestation of riparian sites with the increased length of the river and upstream tributaries.

The rapid proliferation of *P. alni* throughout Europe probably resulted from the increased importance of alders in afforestation activities on wet sites and on former agricultural lands. The combined anthropogenic impacts of

▲ Figure 2—Mature riparian stand of common alder (*Alnus glutinosa*) with sparse, chlorotic and small foliage and crown dieback owing to *Phytophthora alni* root and collar rot.

◀ Figure 3—Mature grey alder (*Alnus incana*), with collar rot caused by *Phytophthora alni*; typical tarry spots at the outer bark and tongue-shaped orange-brown necrosis of the inner bark.

outplanting infected nursery stock and utilizing contaminated river water to irrigate nursery fields were contributing factors (Brasier and Jung 2003, Gibbs and others 2003, Jung and Blaschke 2004). *Phytophthora alni* may also be passively transported on bare-root nursery stock because it is able to adhere to and infect the fine roots of alders as well as adhere to other nonhost tree species exposed to the pathogen.

As short-time control measures, coppicing of infected alder trees and stools is recommended along water courses (Gibbs 2003), but not in infested forest plantations (Jung and Blaschke 2006). Some survivors in highly infested common alder stands were shown to be less susceptible

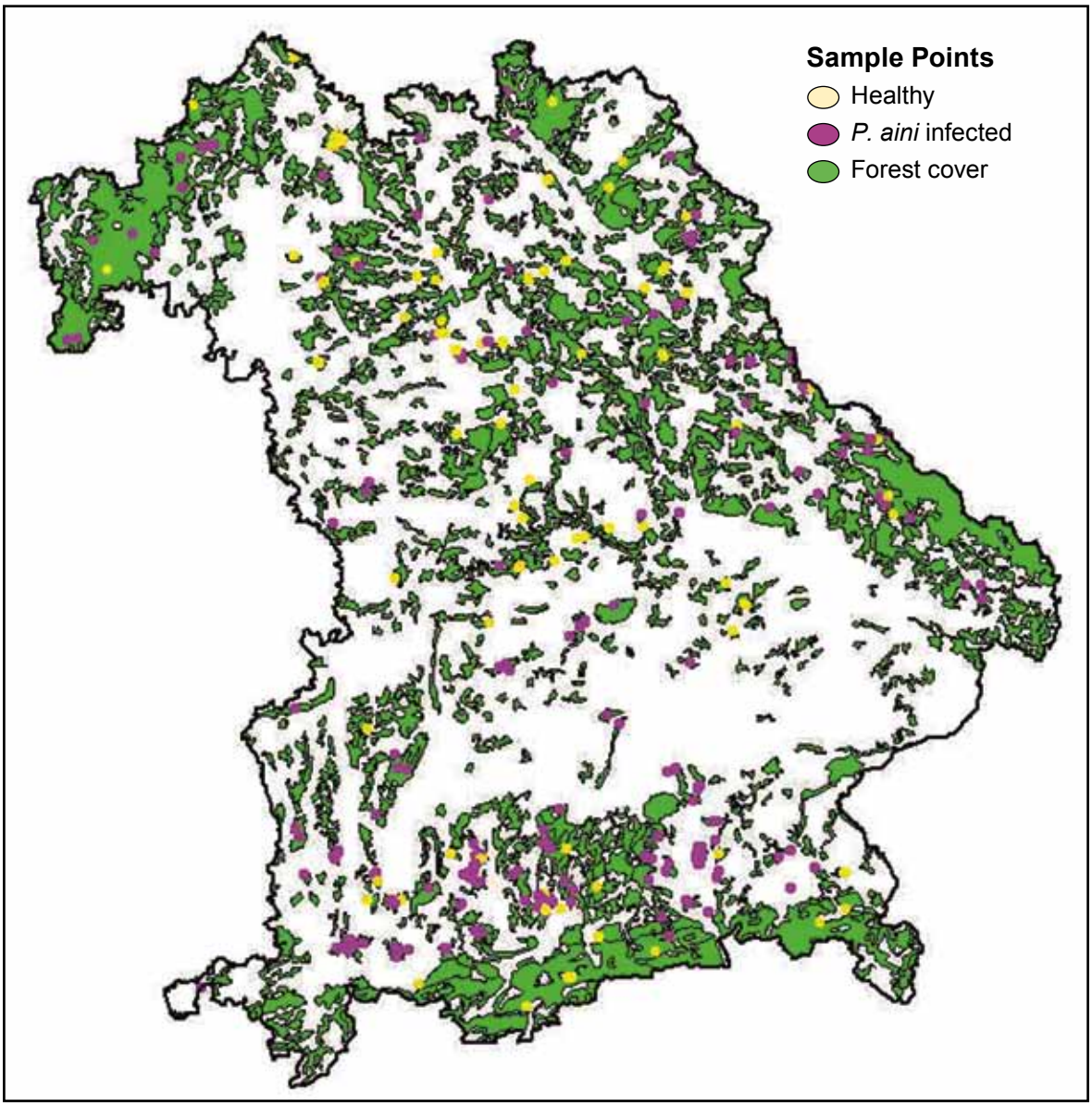

Figure 4—Study area of forested land cover (green) in Bavaria with *Phytophthora alni* infested (pink) and healthy (yellow) sample locations overlain.

to *P. alni* than declining trees, and in the long term, a resistance screening program may help to sustain alders as major components of riparian and swamp forests (Jung and Blaschke 2006).

The Exotic Forest Pest Web site, which is sponsored by the North American Forest Commission (NAFC 2006) lists *P. alni* as a high risk pest to North American forests for its potential to (1) adversely affect the economic trade of alder trees and (2) affect the environment; specifically by changing forest composition, reducing wildlife food and habitat, increasing soil erosion, and changing soil composition owing to alder's nitrogen-fixing capabilities (Cree 1999).

An investigation of the conditions present at 434 sample locations in forested areas in Bavaria (Figure 4) was conducted using classification tree analyses and a tenfold cross validation to estimate the error. Classification and regression trees are a nonparametric iterative approach to compare all possible splits among the independent

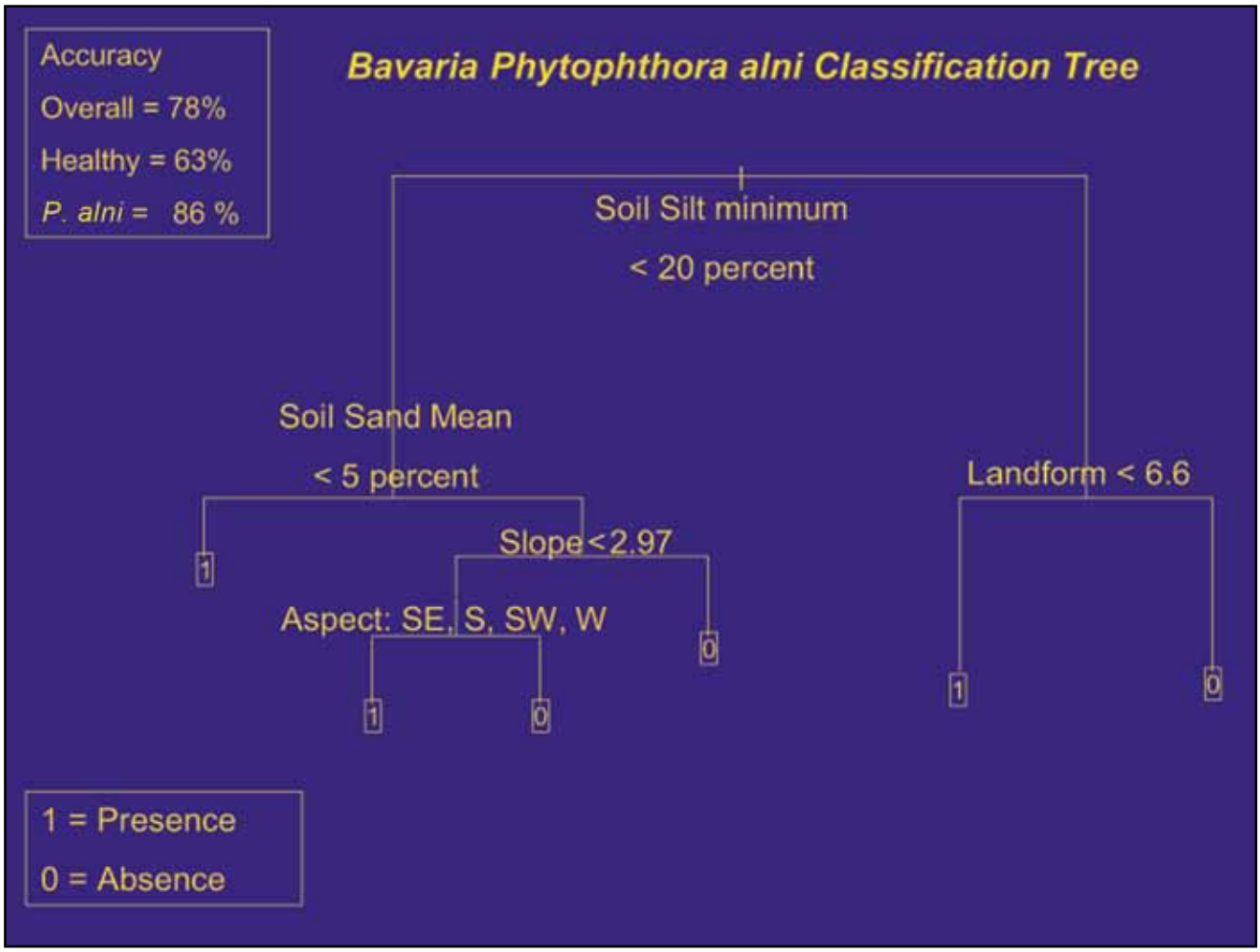

Figure 5—Classification tree model for presence and absence of *Phytophthora alni* in forested areas in Bavaria.

variables using a partitioning algorithm that maximizes the dissimilarities among groups. Classification trees are best used with binary data and regression trees with continuous data. Advantages of using decision trees such as classification and regression trees include the nonparametric nature of the model, ease of interpretation, and the robustness of the test (De'ath and Fabricius 2000). Decision trees have been successfully developed recently for (1) modeling landscape dynamics of the spread of *P. ramorum* (Kelly and Meentemeyer 2002), (2) mapping hemlocks via tree-based classification of satellite imagery and environmental data (Koch and others 2005), (3) predicting the presence and absence of lichen and past fires in Jalisco, Mexico (Reich and others 2005), (4) developing a spatial model for estimating fuel loads in the Black Hills, South Dakota (Reich and others 2004), and 6) developing a methodology to predict oak wilt distribution in Minnesota and Texas (Downing and others 2007).

In this study, rules from the classification tree were used to create the potential distribution surface for Bavaria. Another potential distribution model, a Multicriteria model (Eastman 2001, Eastman and others 1995), was created for the globe using both the rules from the Bavarian classification tree, and additional parameters established with expert knowledge. Global susceptibility surfaces, such as the *P. alni* surface, may be used to illustrate the need for a pathway approach to regulate nursery stock and for host species resistance testing. Multicriteria models have been helpful to produce pest-risk maps for forested land in the United States (Krist and others, this volume).

Table 1—Bavarian independent variables used to produce a potential distribution for *Phytopthora alni* in Bavarian forested areas

A. Aspect: was derived via the DEM surface. **(DEM: Digital Elevation Model) surface.** The DEM surface was used to create ancillary data: slope, aspect, and landform. The DEM was created from the Shuttle Radar Topography Mission (SRTM) in February 2000. SRTM was a joint project between the National Geospatial-Intelligence Agency and the National Aeronautics and Space Administration. The DEM surface was obtained and distributed by the U.S. Geological Survey Earth Resources Observation and Science (EROS) Seamless Data Distribution System (http://seamless.usgs.gov)]. The cell values of zero slope (flat) are assigned an aspect of -1. Therefore, the continuous aspect grid was reclassed to eight basic cardinal directions. Plus another class for zero slope.

B. Soil Fraction/Texture Percent: Soil fraction data were obtained as a soil polygon shapefile from the German **Federal Institute for Geosciences and Natural Resources**. Soil fraction percentage pertains to the volume amount by soil type (sand, silt, and clay) found in the soil sample. The percentage of all three soil fractions sums to 100 percent. To capture the variance of each soil type, three categories of soil fraction percentage were created for each soil type: (1) the minimum soil fraction value for each soil type, (2) the mean soil fraction value, and (3) the maximum soil fraction value. With three data sets included for each of the three soil types, there were a total of nine soil data sets used in the analysis.

C. Landform Index: Landform was derived via the DEM. Landform is independent of slope and created using a custom ArcView Avenue application. The application uses an irregular 3 by 3 kernel, where positive landform values indicate concavity, negative values indicate convexity, and a zero value indicates flat terrain (McNab 1989).

D. Normalized Difference Vegetation Index (NDVI): The NDVI was created from 250-m Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data. The MODIS data was obtained from the Remote Sensing Applications Center (RSAC) in Salt Lake City, Utah. Personnel at RSAC downloaded an archived Bavarian MODIS image and performed the NDVI model. The values of NDVI relate to the relative greenness of the vegetation.

E. Slope: Slope was created using the "Derive Slope" function in the ArcView 3.3 Spatial Analyst extension coupled with the DEM surface. Slope units were degrees.

Methods

Between the spring of 2003 and the winter of 2006, a total of 307 *P. alni* infested and 127 healthy/noninfested alder tree locations were sampled in forested areas in Bavaria (Figure 4). Among the 307 infested sites, there were 232 points where alder trees had been planted, and 75 points where alders were naturally occurring. Of the 127 healthy sample points, 38 were planted and 89 had natural alder growth. A geographic information system sample point theme of the dependent variable was created containing all 434 sample point locations for analysis in the classification tree.

Thirteen independent variable raster data sets were used in the Bavarian classification tree analysis (Table 1). Specifically, these were twelve 93-m physiographic data sets including nine soil texture components (minimum, mean, and maximum percentage values for sand, silt, and clay polygons), aspect, slope, and landform an index of concavity and convexity. The 13th data set was the Normalized Difference Vegetation Index (NDVI) calculated from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery at 250 m. Numerical values were extracted from each of the independent variable grids at each of the sample locations from the sample point theme. These values were then used to compose the spatial information database that was exported to S-PLUS© statistical software (S-PLUS©, Statistical Sciences 2000) for analysis. The independent variables selected by the classification tree were silt, sand, slope, aspects that were Southeast, South, Southwest, and West, and the landform index.

The default S-PLUS© validation technique, tenfold cross validation, was used to prune the tree to avoid overfitting the classification tree model to the Spatial Information Database. The tenfold cross validation was used, as it does not rely on an independent data set and can identify the optimum tree size for minimizing prediction errors.

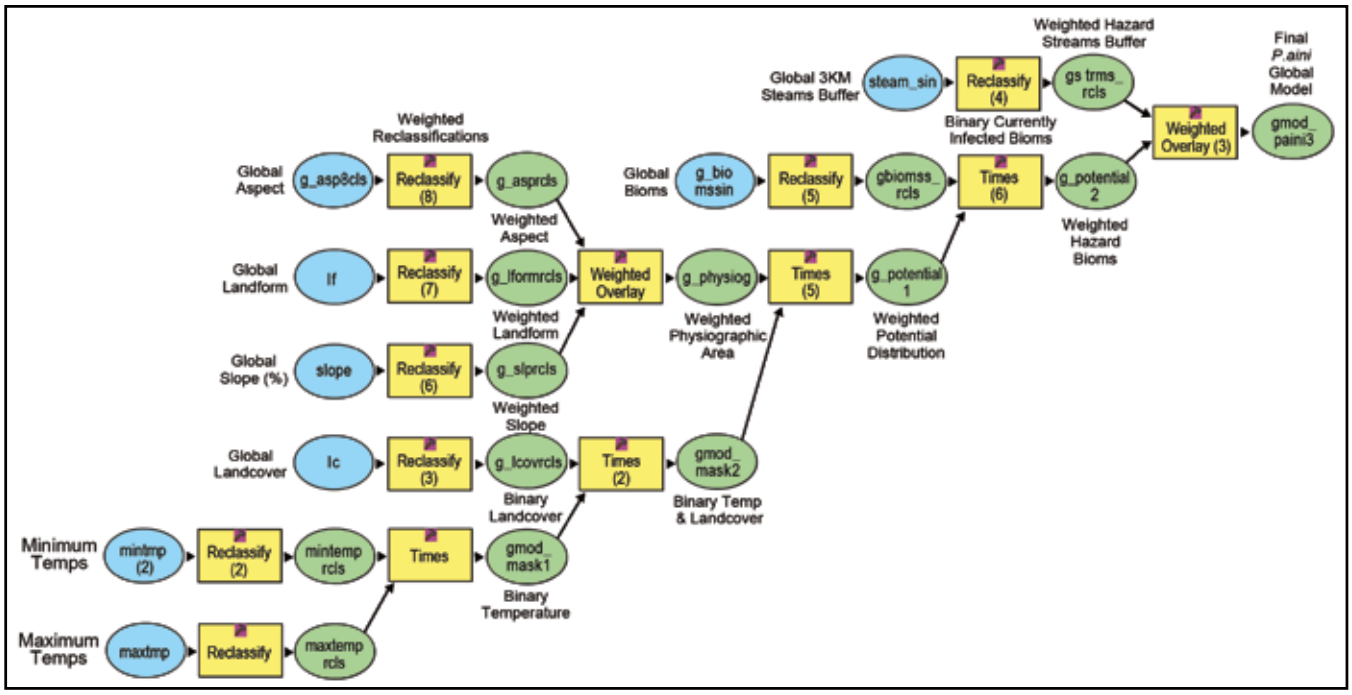

Figure 6—*Phytophthora alni* multicriteria model for the globe.

Based on the results of the classification tree analysis (Figure 5), conditional statements (CON statements; ESRI ArcView, 2000) were used to create a binary *P. alni* potential distribution (i.e., presence and absence) surface for the forested areas in Bavaria. The significant independent variables selected by the classification tree, as well as the decision tree rules (e.g., threshold values taken at the tree nodes), were the input for the CON statements.

Only three of the independent variables that were selected by the Bavarian classification tree were available globally. These were slope, aspect, and the landform index. To see how the rules would change given only the three independent variables, a second classification tree was developed for Bavaria using only those three data sets. This second model had limited utility as it overpredicted the presence of *P. alni*, predicting more than 90 percent of the study area to have *P. alni* present. Still, the rules from the second model did provide some additional insight regarding the broader range of conditions within which *P. alni* might be present. Therefore, the rules from both the original as well as from the second model were combined, along with additional expert knowledge, in a final multicriteria model to create a global susceptibility surface for *P. alni*.

To develop the multicriteria susceptibility model for the globe (Figure 6), the unique numerical values from each criterion had to be standardized. Therefore, each data set was reclassified using a hazard ranking of 0 to 10. The decision rules from both classification trees as well as additional expert knowledge were used as a guide in setting the hazard rankings.

Areas where alder and *P. alni* could not grow were eliminated from the global analysis by creating masks from climate and landcover data. To determine temperature thresholds for the climate mask, an investigation of *Alnus* species was conducted. It was determined from frost hardiness and heat/drought hardiness zones for all alder species that alder does not survive temperatures +/- 40 degrees Celsius.

In addition, lab results performed by Dr. Jung indicated that soil temperatures greater than 32 degrees Celsius prevent the survival of *P. alni*. Although soil temperature data is not available, a regression formula (Temperature MAX threshold value = (Soil Temperature MAX threshold value - intercept estimate)/Regression Coefficient Estimate), was applied to determine that 32 degrees Celsius equates to air temperatures of 34 degrees Celsius.

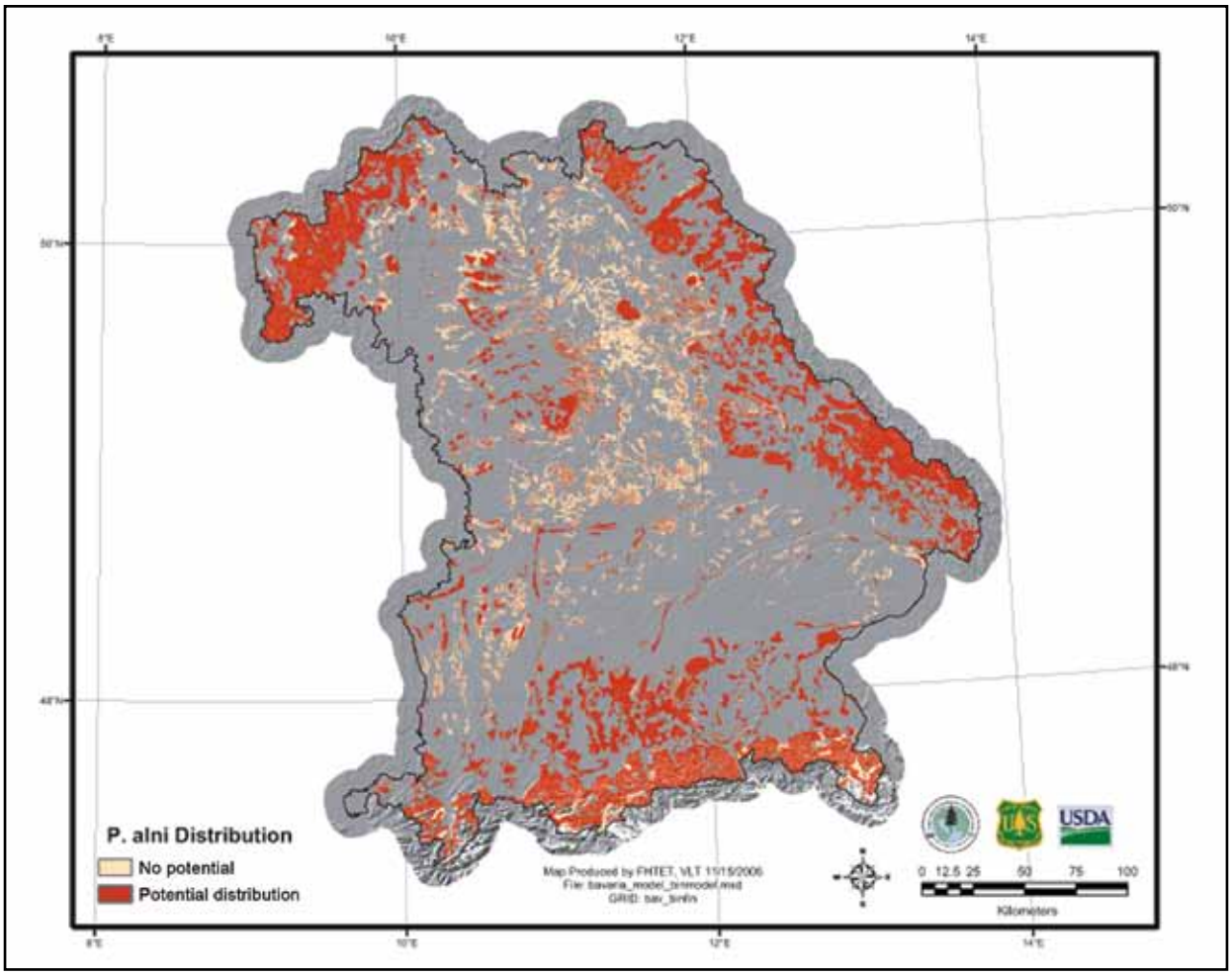

Figure 7—Potential distribution of *Phytophthora alni* (presence and absence) for all forested areas in Bavaria.

Consequently, areas with temperatures less than -40 degrees Celsius and greater than +34 degrees Celsius, as well as areas that could not support alder such as tundra, bare ground, and bodies of water, were removed from further analysis. The binary climate and landcover masks were combined by multiplying both surfaces together to create a combined binary temperature and landcover mask. The resulting mask was combined again in a weighted overlay with the reclassified criteria to produce a potential global distribution.

Because slope predicted most of the variability in the classification tree, it was weighted at 50 percent; aspect and the landform index were both weighted at 25 percent.

To produce the final global susceptibility surface, areas that were identified in the global distribution as having a potential for a *P. alni* infestation were classified according to hazard. Biome and stream data were combined in an equal weighted overlay to assign a hazard ranking. The hazard ranking was based on each pixel's occurrence within ecological biomes similar to the biomes where *P. alni* presently occurs, as well as its proximity to streams. Thus, pixels within the selected biomes were assigned hazard rankings based on their proximity to streams. A set of three global stream buffers at distances of 1km were used to assign the hazard rankings. Pixels that had the potential for infestation were given a high hazard ranking if they fell within 1 km of the stream. Those pixels between 1 and 2 km were assigned a medium potential hazard, and pixels between 2 and 3 km from the stream were assigned a low potential hazard. Pixels that were found greater than 3 km

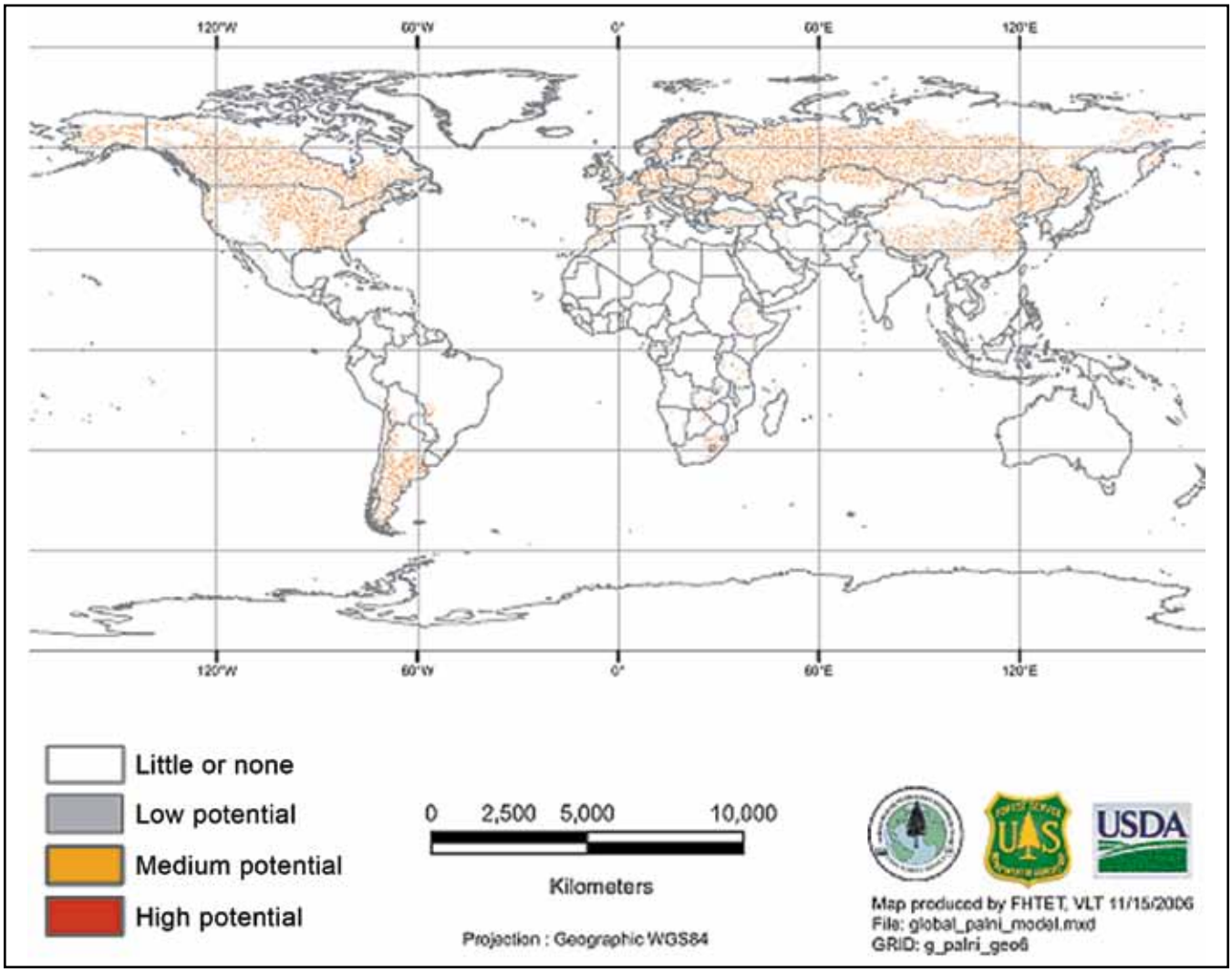

Figure 8—The final global susceptibility surface had 27, 835, 766 km^2 of suitable area where alder and *P. alni* could survive.

from a stream or outside the selected biomes were given a hazard ranking of little or no potential hazard.

Results

For the original Bavarian model: of the 19 620 forested km^2 assessed in Bavaria, approximately 14 015 km^2 (71.43 percent) were modeled to have a high potential for *P. alni* root and collar rot, and 5604 km^2 (28.56 percent were modeled to have a high potential to remain healthy (Figure 7). Seven terminal end nodes were used and accounted for 78.34 percent of the variability. The tenfold cross validation gave a higher accuracy for predicting the 307 *P. alni* infested sites at 86 percent, and showed 63 percent accuracy in predicting the 127 healthy sites. The independent variables important in predicting the presence or absence of *P. alni* were minimum silt fraction values less than 20 percent (range = 0 to 80 percent), mean sand fraction values less than 5 percent (range = 0 to 93 percent), slope less than 2.97 degrees (range = 0 to 30.74 degrees), aspects that were Southeast, South, Southwest, and West, and the landform index less than 6.6 (range = - 15.20 to + 21.60; < 0 = concave; 0 = totally flat; > 0 = convex) (Figure 5).

For the second Bavarian model, with only the three independent variable data sets that are available globally being used, 14 terminal end nodes accounted for 77.19 percent of the variability. The tenfold cross validation still

showed a higher accuracy for predicting the 307 infested sites at 92.51 percent, but only 40.16 percent accuracy in predicting the 127 healthy sites. As expected, all three of the independent variables were used to predict the presence or absence of *P. alni*, but, in this model, slopes less than 19.57 degrees had a higher probability for infestation, and the East aspect was selected in addition to the four aspects that had originally been selected. Also, landform indexes less than 6.2 had a higher probability of infestation.

The final global susceptibility surface had 27,835,766 km^2 of suitable area where alder and *P. alni* could survive (Figure 8). Of that area 1,482,487 km^2 (5.33 percent) were highly susceptible to *P. alni*; 3,930,660 km^2 (14.12 percent) had a medium susceptibility; 5,721,467 km^2 (20.55 percent) had a low susceptibility; and 16,701,152 km^2 (60.00 percent) had little or no susceptibility.

Discussion

The original Bavarian classification tree identified five ecological factors important in the distribution of *P. alni*. Where these factors occur together in the environment, the likelihood of infection is increased. Specifically, where silt minimum values are less than 20 percent, and sand mean values are less than 5 percent, the probability of a *P. alni* infection is high. When silt minimum values are less than 20 percent, and sand means are greater than 5 percent, the site is more likely to have *P. alni* infections if slopes are less than 2.97 degrees and have warmer aspects. Sites with a landform index measure of less than 6.6 (concave, flat or slightly convex) also have an increased probability of a *P. alni* infestation. These results make biological sense. Areas with poor drainage and warmer aspects provide an optimal environment for the pathogen to flourish, as will sites with fairly flat or concave physical structure. Conversely, areas with less clay and more silt or sand will drain better, as will sites with steeper slopes and convex landform. These types of sites will not provide a wet environment for this waterborne pathogen to form sporangia and release zoospores that are essential for the spread and infection of *P. alni*.

Not all of the five ecological factors identified as being important by the first Bavarian model for predicting the distribution of *P. alni* were available for the global model. A second model for Bavaria, which utilized only the three data sets that were available globally, demonstrated the limitations of modeling invasive species at a global scale without appropriate data. The limitation most notable was the soil texture data because it was selected by the first Bavarian model as the most important variable for predicting the presence and absence of the soil-borne pathogen *P. alni*. In addition, data was not available for (1) forest species type (i.e., distribution of the individual alder species), and (2) susceptibility of North and South American and Asian alder species to *P. alni*. We addressed forest species type by keeping our analysis near and around streams and flood plains where most alders tend to grow. We also looked at the temperature range, eliminating areas with temperatures that were too cold or hot for alder and *P. alni* survival. Although we made compromises to work within the data limitations, this work emphasizes the need for quality spatial environmental data at the global scale.

Since planting infected nursery stock is one of the primary pathways by which *P. alni* has been spread, we were careful to consider the social or cultural habits in association with outplanting alder trees. Of particular concern was the outplanting of infected alder trees in respect to elevation. At higher elevations, alder trees are planted much less frequently than at lower elevations. Yet, it has been observed by the Jung that where *P. alni*-infected alder was planted at higher elevations, those sites have become infested and further contribute to infections downhill and downstream. Because alder was rarely planted at higher elevations, *P. alni* was much less prevalent on higher elevation sites. We therefore assumed that the model would be biased toward selecting elevation as an important variable for predicting presence and absence. Consequently, elevation was not used in the model.

A higher accuracy was attained for predicting the *P. alni*-infested sites than for predicting healthy sites. This is likely an outcome of having three times more infested than healthy sample locations. Had we sampled a greater number of locations for the healthy condition, it is likely that the accuracy for predicting healthy sites would improve.

Of the 127 healthy alder tree locations collected between 2003 and 2006, some sites may have changed in

status. Some of the sites that were not infested by 2006 may become infested in the future. These are problems one would expect in attempting to model a species that is unlikely to have been in existence before the 1980s (Gibbs and others 2003, Jung and Blaschke 2004) and has not yet completely expanded into its potential range. With no complete range map for *P. alni*, the Bavarian model provides managers worldwide with useful decision rules and a data mining tool for estimating the susceptibility of their resources to *P. alni*.

Because all of the applicable variables from the first Bavarian model are available in data sets for the United States, the extrapolation of the Bavarian model to forests in the United States should demonstrate the specific improvement that can be gained by applying the appropriate data sets identified by the Bavarian model.

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Assessing Insect-Induced Tree Mortality Across Large Areas With High-Resolution Aerial Photography in a Multistage Sample

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Abstract

In recent years, unprecedented tree mortality has occurred throughout the national forests owing to insect infestations and disease outbreaks. The magnitude and extent of mortality, coupled with the lack of routine monitoring in some areas, has made it difficult to assess the damage, associated ecological impact, and fire hazard in a timely and cost-effective manner. To aid forest managers in assessing the damage, a cost-effective multistage sampling method, using high-resolution digital aerial photography, was developed to estimate overall mortality across large areas. The method was tested within a 332,000-acre piñon/juniper woodland west of Flagstaff, Arizona, within the Kaibab National Forest. Piñon pine mortality caused by piñon ips bark beetles (*Ips confusus* (LeConte)) was assessed from high-resolution digital aerial imagery within percent-cover strata with the use of a digital dot grid. The sample revealed that dead trees covered 7.0 ± 0.3 percent of the study area. As a percentage of total tree cover, 20.0 ± 0.8-percent mortality had occurred. The cost to obtain this estimate was approximately $0.04 per acre.

Keywords: Dot grid, imagery, *Ips confusus*, pinyon, remote sensing, sample.

Introduction

Over the past century, stand density and fuel loading have increased in forests and rangelands throughout the United States, leading to a general decline in ecosystem health. The weakened condition of the forests and rangelands, coupled with drought stress in the Western United States, now place nearly 200 million acres of Federal forest and rangeland in the contiguous United States at risk of epidemic insect and disease outbreaks and catastrophic wildfires (USDA and USCI 2004). In many areas, devastating wildfires and unprecedented insect and disease outbreaks have already occurred.

To address the threat and impact of fire, insects, and diseases to the Nation's forests and rangelands, the U.S. Federal Government launched the Healthy Forests Initiative (HFI) in 2002 and enacted the Healthy Forests Restoration Act (HFRA) in 2003. Primary goals of the HFI and HFRA are to facilitate, expedite, and provide national guidance on hazardous-fuel reduction and ecosystem restoration. In areas where insects and diseases have already caused extensive tree mortality, the HFRA calls for accelerated information gathering on the impact of these mortality agents (USDA and USDI 2004). However, collecting information on the extent and severity of mortality in a timely and cost-effective manner can be very difficult because of the vast acreages that are affected, coupled with the lack of routine monitoring in some areas. In some cases, the extent of mortality is so great that even traditional assessment methods such as aerial sketch-mapping become impractical in terms of time and cost. An efficient and cost-effective alternative assessment method is needed.

One possible alternative is to sample rather than map mortality. Unlike aerial sketch-mapping, which produces a map, but no quantitative measure of mortality, a sample provides a quantitative measure of mortality, but no map. Not all sample designs are efficient or cost-effective, but some have the potential to be less costly and time consuming than traditional methods of assessing mortality. A multistage sample, for example, is one type of sample design

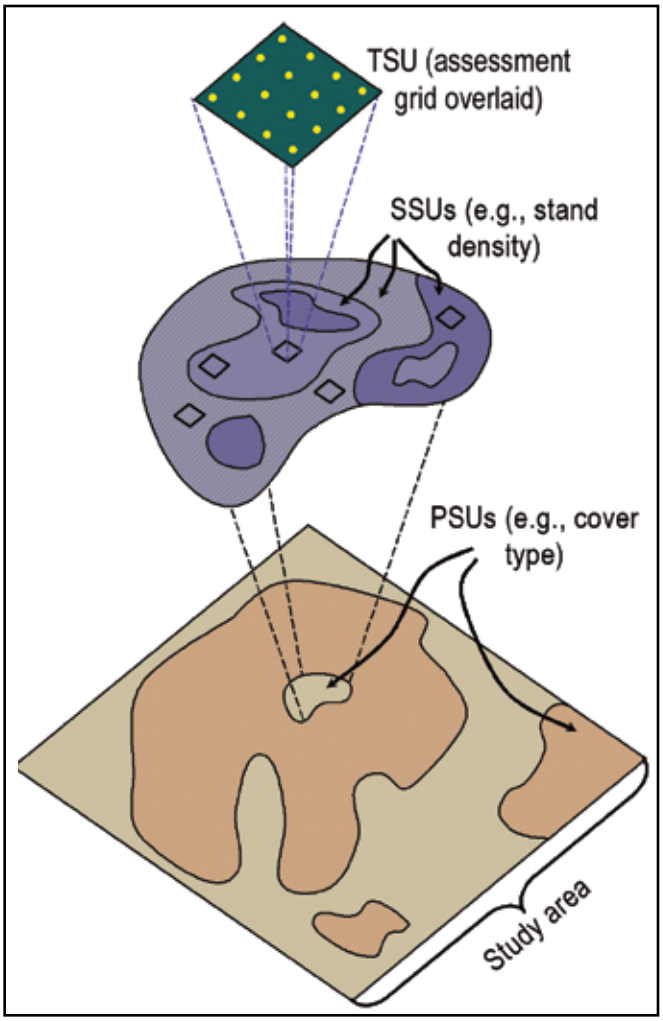

Figure 1—A common multistage sample design defines final sampling units in three consecutive stages: primary sampling units (PSUs), secondary sampling units (SSUs), and tertiary sampling units (TSUs).

that attempts to optimize sampling efficiency. Sampling efficiency is increased by constraining final sampling units to fall within only certain subsections or regions of a study area rather than distributing them across the entire area. Assessing groups or clusters of sample locations is generally easier and less time consuming than assessing widely dispersed sample locations.

In a multistage sample design, a study area is initially partitioned into coarse subunits, called primary sampling units (PSUs). A subset of PSUs is selected and subdivided into secondary sampling units (SSUs). This process of selecting and further subdividing sampling units may be repeated as often as necessary, but a three-stage design is common (Figure 1). In the final stage of the sample, a subset of the previous stage's sampling units are selected and sampled or assessed. From these samples, the variable of interest can be estimated for the entire study area (Ciesla 2000, Schreuder and others 2004).

The dimensions and layout of sampling units can be arbitrary; however, it is generally advantageous to use strata correlated with the variable of interest as sampling units, particularly in the early stages of the design. Sampling within wisely chosen strata allows a multistage sample to take advantage of known sources of variability in the population and can greatly increase the precision of the estimate. When assessing tree mortality, possible strata might include cover type, stand density, elevation, slope, aspect, soil type, proximity to water, and others.

Multistage sample designs have been used previously to inventory timber, estimate tree mortality and volume loss caused by insects in conifer forests, and estimate tree mortality caused by diseases (Ciesla 2000, Langley 1971, Munson and others 1985, White and others 1983). Ciesla (2000) reviewed an assortment of aerial photography-based multistage forest inventories. Typically, these inventories used vegetation type or tree mortality or both as initial-stage strata. Mortality strata were obtained by aerial sketch-mapping or from complete coverage aerial photography. Subsequent stages in these surveys involved collecting aerial photography over plots within the PSU strata. In most of the surveys, the third stage consisted of further subdividing the SSUs into tertiary sampling units (TSUs). A subset of the TSUs was then ground sampled.

Although samples are less costly and time consuming than censuses, multistage samples based on aerial photography and manual photo interpretation can still be expensive and time consuming. Replacing traditional aerial photography in multistage samples with digital aerial and satellite imagery can potentially reduce survey time and related costs. The cost of digital imagery continues to decrease, and economical, yet powerful computers and image processing software can now automate some of the tasks traditionally done by hand. In addition, some field assessments can be greatly reduced by analyzing very high-resolution imagery acquired over the final sampling units.

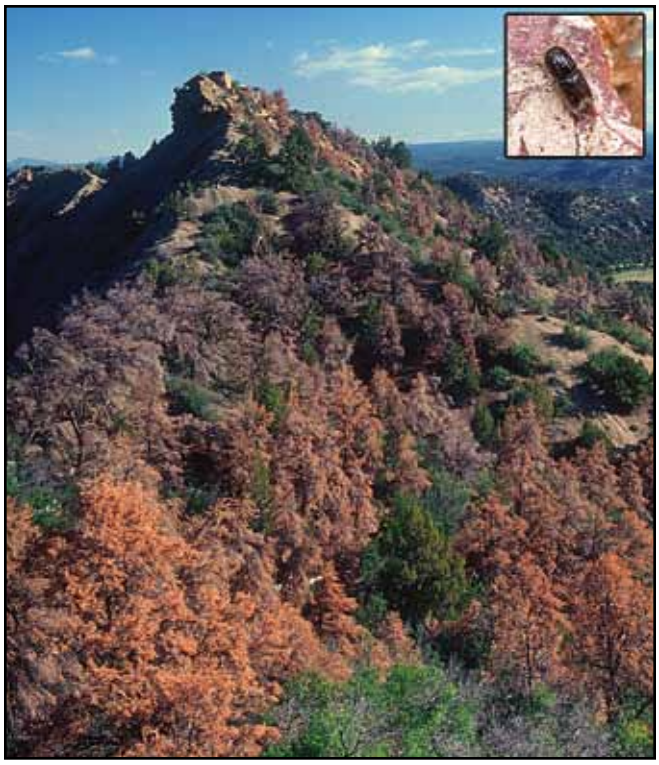

Figure 2—Piñon pine mortality caused by piñon ips beetles (see inset). (Photograph courtesy of William M. Ciesla, Forest Health Management International, Bugwood.org)

To aid forest managers in assessing the severity and extent of widespread tree mortality, the USDA Forest Service Remote Sensing Steering Committee sponsored a pilot study to develop a cost-effective, rapid, and statistically rigorous multistage sample design incorporating digital remotely sensed imagery to quantify tree mortality across large geographic areas. The method was evaluated in a piñon pine/juniper woodland.

Case Study—Assessing Piñon Pine Mortality

Beginning around 2002, extensive piñon pine (especially *Pinus edulis* Engelm. and *P. monophylla* Torr. & Frem.) mortality appeared throughout the Western United States. Dense stocking and sustained drought weakened the defenses of the pines, making them highly susceptible to attack by piñon ips bark beetles (*Ips confusus* (LeConte)) and other insects, as well as infection by black stain root disease (*Leptographium wageneri* (Kendrick) Wingfield) and other disease agents. Insect feeding and diseases destroy and clog the conductive tissues of the trees, causing them to die. The piñon ips beetle, the most important mortality-causing agent of the recent mortality event, is a native species that typically plays an important role in maintaining healthy forests by removing stressed or injured trees. This process thins the forest and reduces competition for water, nutrients, and light. Healthy trees are generally unaffected by the beetles. However, the abundance of drought-weakened trees allowed beetle populations to explode, causing extensive mortality in stressed and healthy trees throughout the piñon/juniper range (Figure 2) (Keyes and Hebertson 2003, Negron and Wilson 2003, Shaw and others 2005).

Because piñon/juniper woodlands are not routinely monitored, assessing the ecological impact of the mortality and the fire hazard it presented became very difficult. Therefore, a rapid and cost-effective multistage sample design incorporating digital aerial imagery was developed to assess tree mortality.

Methods

A multistage sample design was developed and evaluated in a study area located west of Flagstaff, Arizona, in and around the Williams Ranger District of the Kaibab National Forest. The footprint of a SPOT 5 satellite image (60 by 60 km) provided the approximate geographical boundary for the study (Figure 3). In this region, a mixture of piñon pine and juniper (*Juniperus* sp.) dominates lower elevations whereas the upper-elevation forests are predominantly ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.) interspersed with aspens (*Populus tremuloides* Michx.) and higher-altitude conifers.

Stage 1—Piñon/Juniper Woodland Cover Type (PSUs)— The first stage of the multistage sample design consisted of locating the piñon/juniper cover type within the study area to eliminate non-piñon/juniper areas from further analysis. Existing cover-type maps (i.e., from the Gap Analysis Program, the Rocky Mountain Resource Information System, the National Landover Data set, and other sources) were evaluated for this purpose. These data sets were deemed unsatisfactory for this study because changes in cover type from vegetation management activities were sometimes not

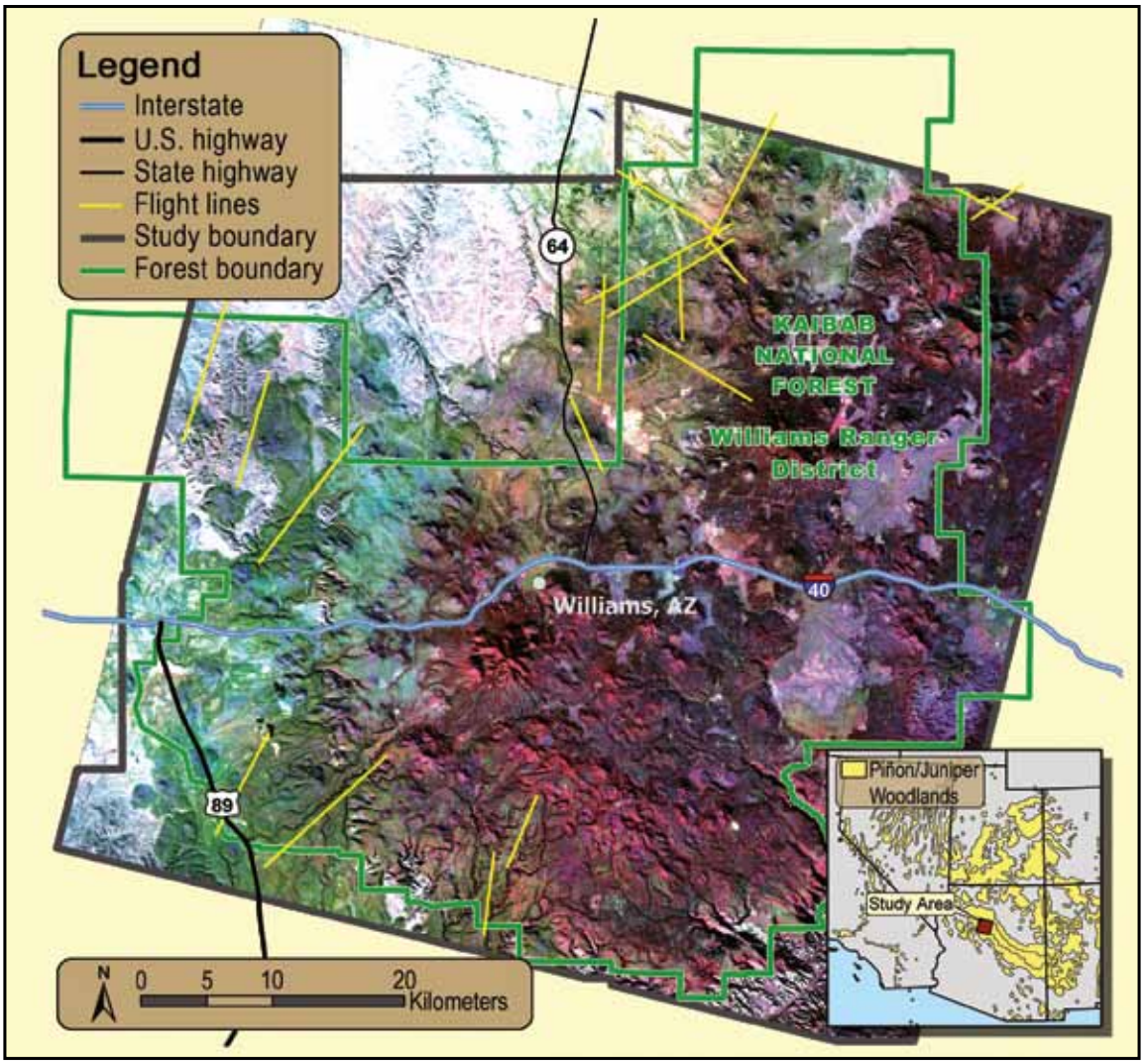

Figure 3—The pilot study area was located west of Flagstaff, Arizona, within the Williams Ranger District of the Kaibab National Forest. A SPOT 5 satellite imagery scene (acquired September 16, 2003)—displayed in false color infrared with topographic enhancement—defined the extent of the study area. Green and blue/green areas are piñon/juniper woodlands, whereas red areas are primarily ponderosa pine forests. Flight lines where airborne imagery was collected are shown as yellow lines.

reflected in these maps and some obvious fine-scale errors were also present. Therefore, a three-class vegetation map (piñon/juniper, ponderosa pine and other conifers, and meadow/bare ground/other) was developed for the study area using image segmentation and regression tree classification (Figure 4) (Hamilton and others 2004). This map formed the PSUs. For this study, the entire 332,000-acre piñon/juniper cover type was advanced to the second stage of the sample.

Stage 2—Percent-Cover Strata (SSUs)— Negron and Wilson (2003) reported that the likelihood of piñon ips infestation increased with stand density in Arizona. To reduce sample variance, this known source of variability was incorporated into the sample design by stratifying the piñon/juniper vegetation class by percent cover. The percent-cover strata became the SSUs. Breaks for the percent-cover strata were based on the broad-level vegetation cover categories established by the USDA Forest Service Existing Vegetation Classification and Mapping

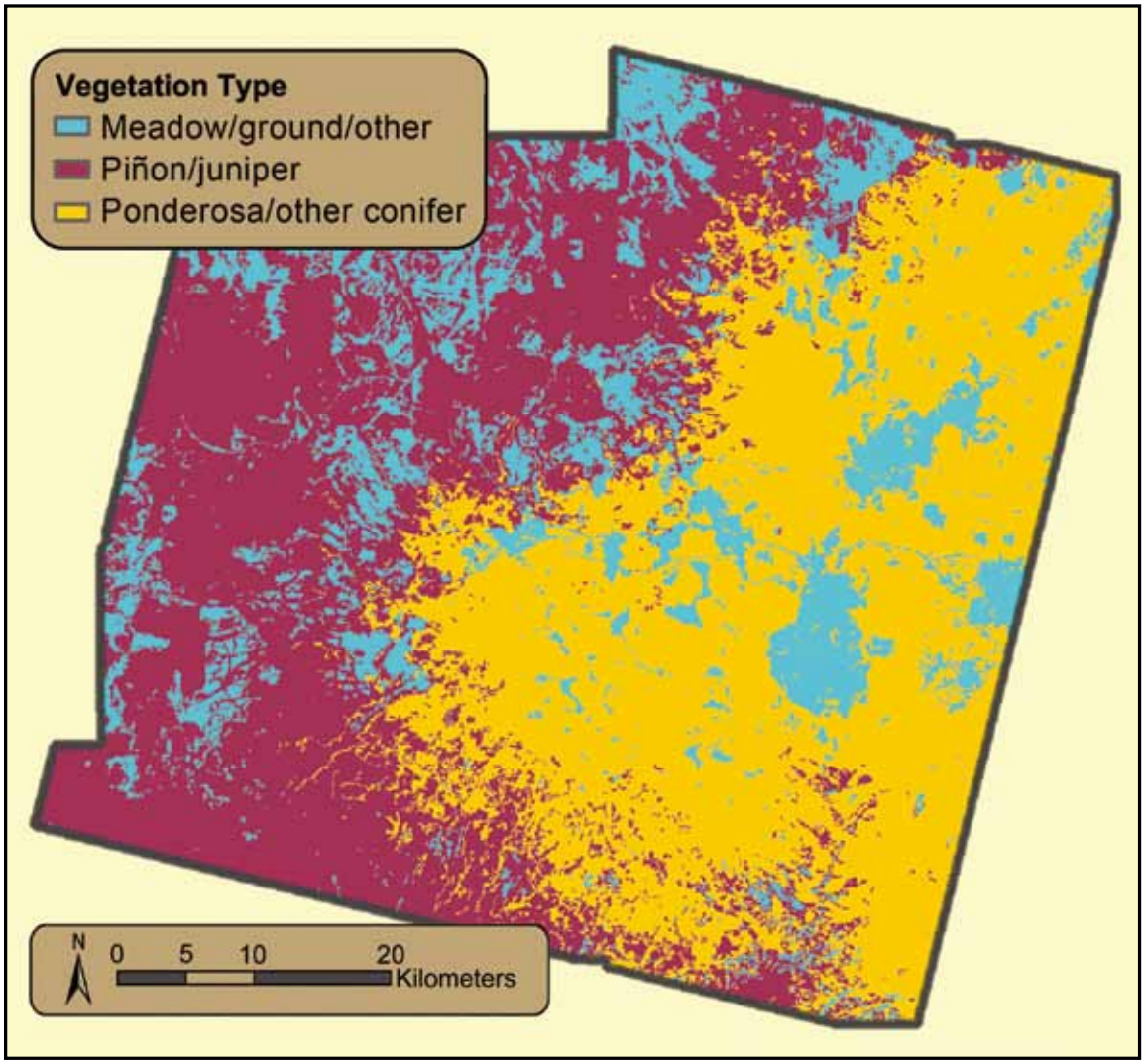

Figure 4—A vegetation-cover map, used to restrict the multistage sample to piñon/juniper woodlands, was created using regression tree classification. This is the first stage of the multistage sample.

Technical Guide (Brohman and Bryant 2005) (Table 1). The first vegetation-cover category (0 to 29.9 percent), was further subdivided into 0 to 9.9-percent and 10 to 29.9-percent categories to refine the SSUs.

Because no existing percent-cover maps were available for the study area, a map was created from 1992 digital orthophoto quadrangles (DOQs). The DOQs were not current, and we anticipated that the mapped percent cover would generally be lower than the actual percent cover. However, as the objective of this exercise was to stratify the study area (not to measure percent cover), relative differences in actual percent cover compared to mapped percent cover would still allow the map to serve its purpose of stratifying the study area. The relative differences in percent cover are inconsequential so long as percent cover and, consequently, mortality, is more homogeneous within than between strata. To create the percent-cover map, a two-class classification (tree and nontree) was created from the DOQs in ERDAS Imagine. Then, for each image segmentation polygon (average size ≈ 2.5 acre) used in the vegetation classification, the percentage of the polygon occupied by mapped trees was calculated (Figure 5). No accuracy assessment was conducted for the percent-cover map. However, final sample results verified that percent

Table 1—Percent-cover ranges of SSU strata and strata acreages within the entire piñon/juniper region and the region of aerial imagery coverage are shown, including proportions by stratum of total study area and aerial imagery coverage for the two regions

Strata	Acreage and (proportion of total area)	
(percent-cover ranges)	Piñon/juniper region	Aerial imagery coverage
0-9.9 percent	36,224 (0.11)	739 (0.10)
10-29.9 percent	108,633 (0.33)	2,376 (0.32)
30-59.9 percent	140,162 (0.43)	3,582 (0.49)
60-100 percent	39,430 (0.12)	642 (0.09)
Total	324,449	7,339

SSU = Secondary Sampling Units.

cover and mortality were more homogeneous within than between strata.

Stage 3—Digital Aerial Imagery Plots (TSUs)— Tertiary sampling units for this study consisted of 60-by 60-m digital aerial imagery plots. Plots were sampled for mortality using a digital dot grid. On March 30 and April 24, 2004, high-resolution digital camera (Kodak Pro Back 645C digital back attached to a Contax 645 medium format camera) imagery was acquired in 18 flight lines at various locations across the study area (Figure 3). The imagery was acquired with an 80 mm lens at an altitude of approximately 1375 m, producing 16-cm spatial-resolution imagery with a swath width of approximately 640 m. The imagery was orthorectified using OrthoBASE in ERDAS Imagine. Thirty TSU plots were randomly located within each percent-cover stratum (for a total of 120 plots) and the geographic boundaries of the aerial imagery. Although the percent-cover strata were not equal in size (Table 1), they were sampled equally to ensure a minimum number of samples in each stratum.

The plot size and dot density were chosen to optimize the accuracy and precision of the sample while minimizing the total number of dots per sample (i.e., minimizing costs). This was accomplished by sampling several areas from each percent-cover stratum using multiple dot grids, ranging in size from 30 by 30 m to 240 by 240 m with dot densities of 364, 648, or 1,012 dots per acre. A plot size of 60 by 60 m with dot density of 364 dots per acre (18 by 18 dots per plot) was considered optimal as the precision of the estimate increased only slightly with increased plot size or dot density or both. The dot grid was created from graphic elements in ArcGIS 8.3, allowing it to be moved easily from one plot to the next by dragging and dropping. Although this graphic dot grid worked well for this study, a new tool for ArcGIS 8.3 and 9.x, Digital Mylar—Image Sampler, was recently developed by the USDA Forest Service Remote Sensing Applications Center and now provides a more automated and user-friendly approach to dot grid sampling (USDA Forest Service 2005).

At each sample location, the dot grid was placed over the high-resolution imagery (Figure 6). The total number of dead-tree, live-tree, and ground hits from the dots was counted. First-year and later mortality were all grouped into the dead-tree category for this study. In this sampling procedure, piñon pines were not distinguished from junipers owing to the difficulty of distinguishing the two species on this imagery by photo interpretation. The proportion of each plot covered by dead trees, live trees, total tree cover (i.e., live plus dead trees), and other (typically bare ground) was calculated from the dot grids by tallying the hits of the individual variables and dividing by the total number of dots in the sample. Subsequently, mean values of these variables were calculated for each percent-cover stratum. The mean proportion of the entire piñon/juniper region (i.e., across all strata) covered by dead trees, live trees, total tree cover, and other was calculated from the estimates of each percent-cover stratum. These estimates were made using a standard weighted disproportionate-strata estimation equation, with the strata areas from Table 1 as weights (Equation 1) (Scheaffer and others 1990). Because relative proportions of strata areas for the entire piñon/juniper region were similar to those falling within the boundaries of the aerial imagery (Table 1), no adjustments were needed to extrapolate the estimate from the extent of the aerial imagery to the entire study area.

$$\hat{p}_{st} = \frac{1}{N} \sum_i (N_i \hat{p}_i) , \qquad (1)$$

where $\hat{p}_{st}$ is the mean across-strata proportion of land area covered by dead trees, live trees, total tree cover, or other;

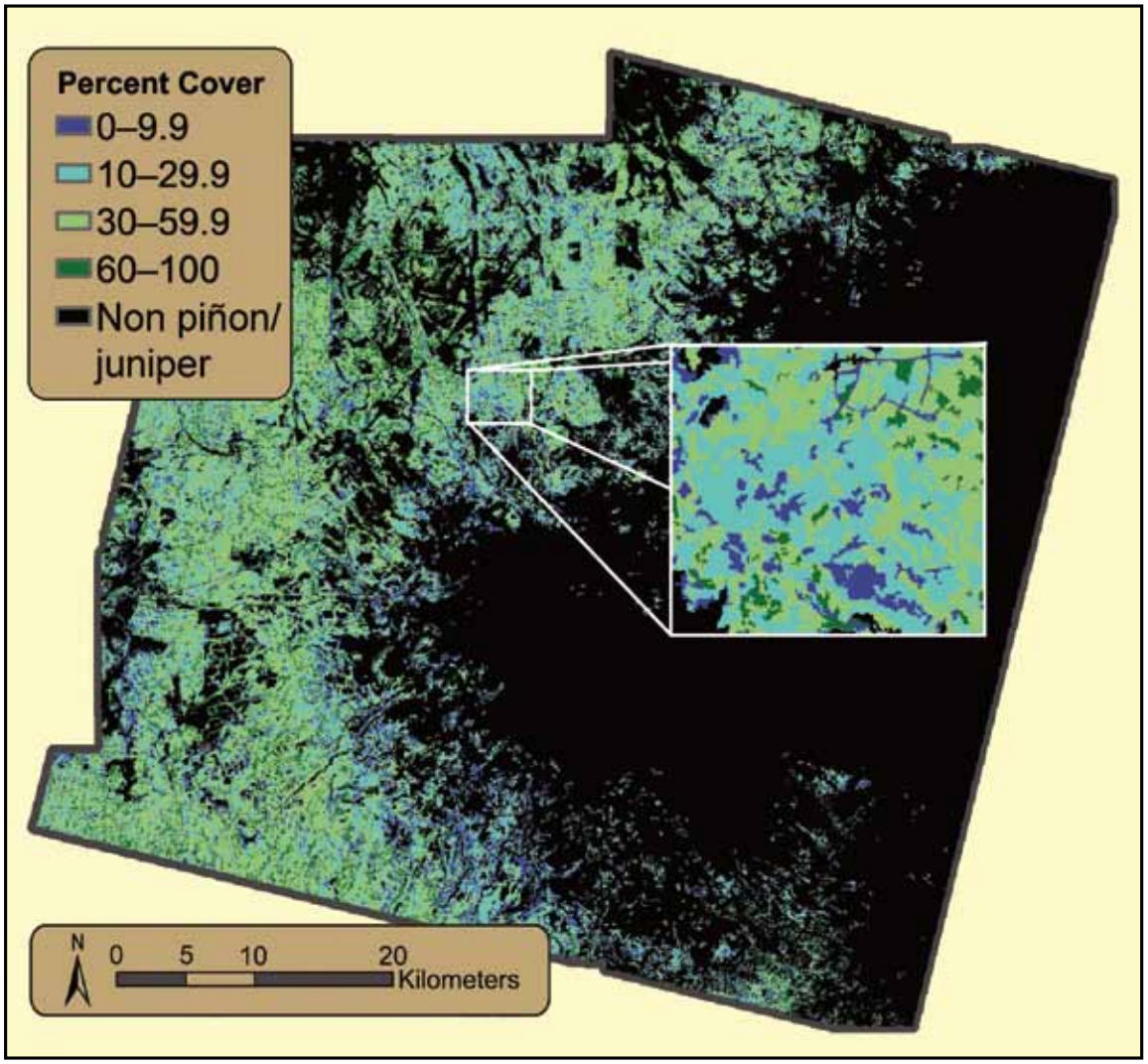

Figure 5—Percent-cover strata for the study area, derived from digital orthophoto quadrangles, were developed for the second stage of the multistage sample and formed the secondary sampling units.

$\hat{p}_i$ is the mean proportion of land area within each percent-cover stratum, indexed by i, covered by dead trees, live trees, total tree cover, or other; N is the total possible number of individual dot samples within the entire study area; and N_i is the weight of the ith percent-cover stratum (i.e., the proportion of possible dot samples within the piñon/juniper forests of the ith percent-cover stratum to the total possible number of dot samples within the entire piñon/juniper forested area).

Standard errors of the across-strata mean proportion estimates were also calculated (Equation 2). From these results, the mean proportions of total tree cover that had died were calculated for each percent-cover stratum as well as across strata for the entire piñon/juniper population.

$$\hat{E}(\hat{p}_{st}) = 2\sqrt{\frac{1}{N^2}\sum_{i}^{n} N_i^2 \left[\left(\frac{N_i - n_i}{N_i}\right)\left(\frac{\hat{p}_i(1-\hat{p}_i)}{n_i - 1,}\right)\right]} \qquad (2)$$

where $\hat{E}(\hat{p}_{st})$ is the error of the mean across strata proportion of land area covered by dead trees, live trees, total tree cover, or other; n_i is the number of dot samples taken from each percent-cover stratum; and N_i, N, $\hat{p}_i$ are as described in equation 1.

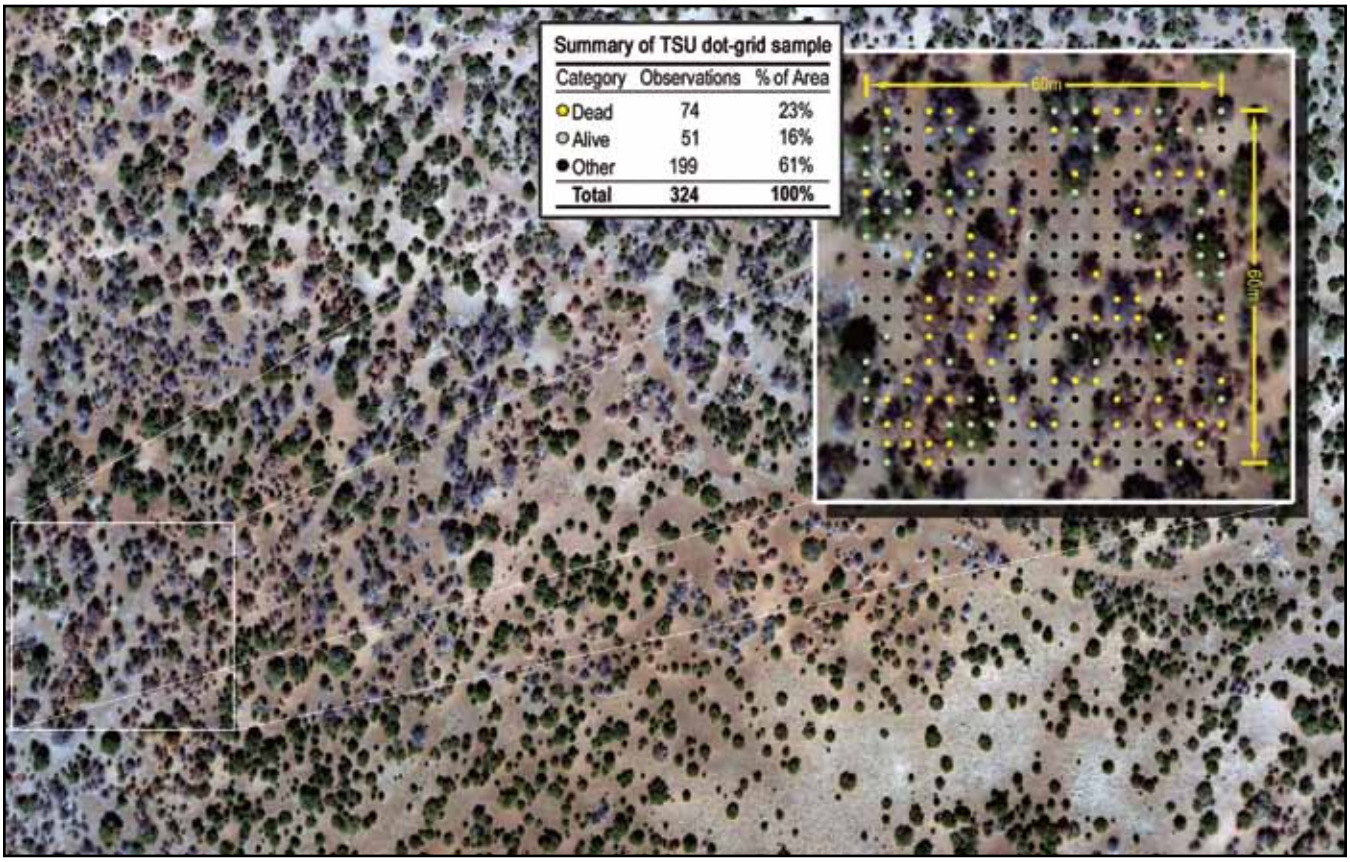

Figure 6—Natural-color, digital aerial imagery with dot-grid sample collected March 30, 2004, over an area of piñon mortality. The inset shows an example of a dot-grid sample of mortality within a 60 by 60 m (approximately 1 acre) tertiary sampling unit (TSU). Observations of dead trees, live trees, and other are color-coded and tallied for the site.

Results and Discussion

Estimates calculated for the entire piñon/juniper region of the study area (across strata) showed that dead tree canopies occupied 7 ± 0.3 percent of the total area as viewed from aerial imagery (Table 2). As a percentage of total tree cover, 20 ± 0.8-percent mortality had occurred (Table 3).

Actual percentage of cover derived from the dot-grid samples often differed from the predefined percent-cover ranges of the SSUs. However, the stratification still served its purpose of reducing sample variance—percent cover and mortality were more homogeneous within than between strata. The results of this study generally support Negron and Wilson's (2003) conclusion that mortality increases with percent cover (Table 3).

Costs to conduct this multistage sample included $5,050 for materials and approximately 30 days of labor (Table 4). If labor were priced at $300 per day, the cost per acre for the 332,000-acre study area would be slightly more than $0.04. These cost estimates do not include the cost of creating a vegetation-cover map to narrow the study region to only piñon/juniper woodlands. It is assumed that sufficiently accurate digital maps of vegetation cover are or will soon be available for most of the Nation.

The cost incurred in this study can serve as a reference point for similar studies in other areas. However, costs can vary greatly depending on location, imagery resolution, size of the study area, and other factors. The cost-per-unit area, for example, is scale dependent—decreasing as the size of the study area increases.

Conclusions

Forests and rangelands throughout the United States are at risk of severe insect and disease outbreaks and catastrophic wildfires. Epidemic insect infestations have already caused

Table 2—Mean proportions of land area comprised of various cover types for each stratum. For each stratum, the mean proportions (±SE) of area (as viewed from aerial imagery) comprised of dead, live, and total tree cover, and ground are shown[a]

Stratum (percent-cover range)	Mean proportion of stratum land area, by type of cover			
	Dead	Live	Total tree cover	Ground
0-9.9	0.021 ± 0.006	0.150 ± 0.018	0.171 ± 0.020	0.829 ± 0.020
10-29.9	0.059 ± 0.015	0.256 ± 0.014	0.315 ± 0.018	0.685 ± 0.018
30-59.9	0.090 ± 0.016	0.319 ± 0.018	0.409 ± 0.016	0.591 ± 0.016
60-100	0.082 ± 0.017	0.336 ± 0.021	0.418 ± 0.018	0.582 ± 0.018
All strata	0.071 ± 0.003	0.281 ± 0.005	0.352 ± 0.006	0.648 ± 0.006

[a] Weighted mean proportions (±SE) for the entire piñon/juniper study area (i.e., across strata) are also provided.

Table 3—For each percent-cover stratum, the mean proportion (±SE) of total tree cover that has died, and mean weighted proportion (±SE) across all strata are provided

Stratum (percent-cover range)	Mean proportion of total tree cover that is dead
0-9.9	0.125 ± 0.031
10-29.9	0.186 ± 0.033
30-59.9	0.221 ± 0.033
60-100	0.197 ± 0.033
All strata	0.196 ± 0.008

Table 4—Approximate material costs and labor for an experienced analyst to conduct a multistage sample to estimate piñon mortality in the Williams Ranger District

Expense item	Labor (days)	Cost
Materials		$5,050
Orthorectification of aerial imagery	9	
Percent-cover stratification	9.5	
Dot-grid sampling	10.5	
Calculating results	1	
Total	30	$5,050

extensive mortality in many of the Nation's forests and rangelands. The severity and large extent of mortality, coupled with the lack of routine monitoring in some areas, has made it difficult to assess the damage, ecological impact, and fire hazard in a timely and cost-effective manner.

The multistage sampling method used in this study offers a statistically rigorous approach to estimate tree mortality across large geographic areas, increase sampling efficiency, and provide a confidence interval about the mean. By using a digital dot-grid to assess mortality from high-resolution aerial imagery, the need for time consuming and costly field assessments was eliminated. The use of imagery also allowed samples to be drawn from remote areas that would have been prohibitively time consuming to sample in the field. This method was tested over a 332,000-acre piñon/juniper woodland west of Flagstaff, Arizona, but the technique is applicable to many other forest types impacted by insects and diseases. The multistage sample estimated that, as of spring 2004, dead-tree canopies occupied approximately 7 percent of the area within the piñon/juniper woodlands of the Williams Ranger District. Relative to the total tree cover, approximately 20-percent mortality was sustained. For the piñon/juniper study area, the cost to estimate mortality was approximately $0.04 per acre. In other areas, the cost per unit area to conduct a similar study could vary greatly depending on the location, size of the study area, and imagery requirements.

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Modeling Potential Movements of the Emerald Ash Borer: the Model Framework

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Abstract

The emerald ash borer (EAB, *Agrilus planipennis* Fairmaire) is threatening to decimate native ashes (*Fraxinus* spp.) across North America and, so far, has devastated ash populations across sections of Michigan, Ohio, Indiana, and Ontario. We are attempting to develop a computer model that will predict EAB future movement by adapting a model developed for the potential movement of tree species over a century of climate change. We have two model variants, an insect-flight model and an insect-ride model to assess potential movement.

The models require spatial estimates of EAB abundance and ash abundance. The EAB abundance map shows a zone of initial infestation in the western suburbs of Detroit, with ash trees first dying about 1998. The fine-scale (270-m cells) ash basal area maps show highly variable values, but woodlots often have very high levels of ash. At the coarse scale (20-km cells) for the Eastern United States, available ash is high throughout the northern part of the country.

With the flight model, probability of movement is dependent on EAB abundance in the source cells, the quantity of ash in the target cells, and the distances between them. With the insect-ride model, we used geographic information system data to weight factors related to potential human-assisted movements of EAB-infested ash wood or just hitchhiking insects. We are developing a gravity model that considers traffic volumes and routes between EAB source areas and various distances to campgrounds.

Preliminary results from a test strip through northern Ohio show (1) the insect-flight model creates a relative probability of colonization that decreases quickly from the EAB range boundary edge; and (2) the insect-ride model provides occasions for long-distance transport via human-aided dispersals.

Keywords: Ash, dispersal, emerald ash borer, invasive, Ohio.

Introduction

The emerald ash borer (EAB), *Agrilus planipennis* Fairmaire (Coleoptera: Buprestidae), poses a serious threat to all ash trees in North America. The larvae feed on phloem, producing galleries that eventually kill large trees in 3 to 4 years and small trees in as little as 1 year (Poland and McCullough 2006). A native of Northeastern China, Korea, Japan, Mongolia, Taiwan, and Eastern Russia, the species was first identified in the United States near Detroit, Michigan, in July 2002 (Haack 2006). The borer was probably imported into Michigan in the early 1990s via infested ash crating or pallets (Herms and others 2004).

The impact of EAB may be enormous. An estimated 8 billion ash trees exist in the United States, comprising roughly 7.5 percent of the volume of hardwood sawtimber, 14 percent of the urban leaf area (as estimated across eight U.S. cities), and with a value exceeding $300 billion (Poland and McCullough 2006).

Research into the spatial distribution of the host ash species helps us better understand the resource at risk and the potential for EAB spread. The USDA Forest Service's Forest Inventory and Analysis (FIA) units continually conduct inventories across more than 100,000 plots in the Eastern United States (Miles and others 2001). This invaluable data source provides the information critical to the assessment of the ash resource, including the work reported here. For a detailed look, we rely on 30-m Landsat data that have been classified into forest types with associated ground samples to calculate ash content.

There are a variety of approaches for using computer models to predict the risk and spread of invasive insects (e.g., Rykiel and others 1988, Sharov and Liebhold 1998, Sharov and others 1997, Sturtevant and others 2004, Turchin 2003). To summarize, modeling insect movement is a complicated venture, especially in heterogeneous landscapes. BenDor and Metcalf (2006) and BenDor and others (2006) have initiated a dynamic modeling approach to learn more about EAB spread and possible mechanisms to retard it. These authors also call for high resolution data on the ash resource and human-assisted components such as campgrounds to move this work forward. In this paper, we present a slightly different approach using higher resolution databases.

The objectives of this work are to (1) evaluate the ash quantity across the Eastern United States at a coarse level and in Ohio at a fine scale; (2) assess EAB spread and rate of spread through the region so far; and (3) begin to model future spread through the two modeling approaches of insects flying and insects riding with humans.

Methods

Distribution of Ash

Fraxinus (ash) is the only genus that EAB has attacked in North America. There is no observed host expansion. Consequently, we mapped ash availability as a resource for EAB spread, at a coarse resolution for the Eastern United States (20- by 20-km cell) and at a fine resolution for Ohio (30- by 30-m cell size).

Coarse-Level Analysis of Ash for the Eastern United States—
We used FIA data (Miles and others 2001) to determine ash distribution and abundance for 9,782 cells over the Eastern United States. We created these data sets for a climate change atlas (Iverson and others 1999) and have made these data available (Prasad and Iverson 2003). We summed the data for four species of ash that comprise the vast majority of ash in the Eastern United States: *Fraxinus americana* L. (white ash), *F. pennsylvanica* Marsh. (green ash), *F. nigra* Marsh. (black ash), and *F. quadrangulata* Michx. (blue ash). This effort produced maps of relative availability of rural ash (FIA does not sample urban areas well) to the EAB. The methodology used data from the 100,000+ forested plots to calculate the basal area (BA) of ash per plot, then calculated average BA of ash per unit area based on all the plots within the 20- by 20-km cell. One drawback of this methodology is that in some cells with small quantities of forest, no FIA plots were established so that the average ash BA is calculated as zero for that cell. In reality (as seen in the fine-scale analysis), every cell in the Midwest has at least some forest (and, most likely, some ash). Another drawback is that the urban forest resource is underrepresented in the FIA data. (There is an ongoing effort within our group to conduct surveys to better understand the forest resource in certain urban areas.)

The next step was to create a map of percentage of forest cover by 20- by 20-km-grid cell. We acquired classified 30 m Landsat TM-interpreted data from Riitters and others (2002). The data were reclassified into forest or nonforest and tallied by 20- by 20-km cell to yield an estimated percentage of forest cover for each cell.

Data from the average BA map was multiplied by the percentage of forest cover per 20- by 20-km cell, providing an estimate of the total availability of the ash resource to the invasive species, in thousands of square feet of BA per 20 by 20 km.

Fine-Scale Analysis of Ash in Ohio—
For a detailed estimate of ash resource availability in Ohio, we combined estimates of ash BA per FIA plot with a Landsat TM-based classification of forest types. We acquired the landcover data from the Ohio Gap Analysis Program (GAP) (Ramirez and others 2005). This data set contains vegetation classes based on leaf-on and leaf-off imagery from 1999 to 2002 (Ramirez and others 2005), at 30-m resolution. Vegetation classes conform to the NatureServe's Ecological Classification system (Comer and others 2003). We attempted to establish ash percentages for 28 classes, including the following classes important in northwestern Ohio: row crop, open water, low density urban, high density urban, urban forested, grassland, evergreen forest, North-Central Interior Dry Oak Forest and Woodland (CES202.047), North-Central Interior Floodplain (CES202.694), North-Central Interior Wet

Flatwoods (CES202.700), and North-Central Oak Barrens (CES202.727).

To estimate ash BA in each landcover type, 2,298 FIA plots were overlaid on the Ohio GAP data set by Elizabeth LaPoint, FIA geographic information system (GIS) Service Center. Due to the restriction on releasing FIA plot coordinates, Ms. LaPoint performed the overlay and reported the average ash BA per class. However, only a portion of the plot coordinates (ca 40 percent) were global positioning system (GPS) corrected so that locational error is present in the overlay (which caused, for example, some plots to appear in open water). For certain classes, including the urban classes, row crop, and oak barrens, we believed, based on number of FIA plots available and ancillary information, the data reported for southern Michigan by McFarlane and others (2005) better represented the quantity of ash present in the types. So, the McFarlane and others data were substituted for the FIA estimates.

Finally, an EAB habitat availability map was prepared by applying the estimated BA of ash per class. To prepare a smoother map, which was needed for the modeling effort, we calculated the mean ash BA per 270-m pixel (a 9 by 9 cell average). This product was used for mapping and modeling, which requires estimates of ash quantities per cell (see "Modeling Spread in Ohio").

Mapping Estimated EAB Spread, 1998–2005

To model potential future spread and assess observed spread rates, a preliminary map of historical spread was created. For this, multiple data sets and GIS manipulations were used, and for the most part, represent the spread of visible damage to ash trees rather than the initial infestation of EAB. The Michigan Department of Natural Resources (DNR) mapped pest outbreaks, which estimated the range of EAB-damaged ash in 2002 and 2003. These were accepted as accurate. We also used data from interstate highway exit surveys for 2003 and 2004, with 10 ash trees per exit tallied for death/life (irrespective of what killed the ash) by Smitley (2005) and Smitley and others (2005). These data were useful to show where ash death first occurred in the region. A Michigan ash damage survey from September 2004 also was used (Michigan State University, 2006) along with the actual locations and density of extent of known EAB locations as of December 2005, obtained from the Cooperative Emerald Ash Borer Project (2006). In addition, multiple dates of these national EAB positive maps were acquired to detect additional finds temporally. Finally, our own field work on ash tree assessment in northern Ohio and southern Michigan during the summers of 2004 and 2005 yielded additional spatial information, particularly on ash not yet visually affected by EAB. Again, most of the data were based on visual observations of damage, which can be delayed for several years after EAB colonization in otherwise healthy, larger ash trees. It should also be noted that girdled detection trees were used in Michigan in 2004 and 2005, which increased detection capability over that available from visual inspection alone. Thus, this new survey method may have artificially expanded the estimated front in 2004 and 2005 over what would have been detected with only observable symptoms. It definitely expanded the number of outliers detected outside the main front.

Known EAB locations were inputted into ArcGIS (GRID - focalsum commands), and four EAB abundance classes were derived based on the number of EAB positives recorded within three spheres of influence around each point: 1, 2.5, and 5 km. Each 270-m cell within the study area was assigned EAB abundance class 0 (no EAB positives within 5 km), 1 (1 to 5 positives within 5 km), 2 (1 to 3 positives within 2.5 km or 6 to 10 positives within 5 km), or 3 (1 to 38 positives within 1 km, or 4 to 100 positives within 2.5 km, or 11 to 110 positives within 5 km). The resulting map presented the best summary of EAB concentration areas as of December 2005.

Armed with all the above data sets overlaid in ArcGIS, we manually drew estimated boundaries of the EAB-damaged ash front for 2005, 2004, 2001, 2000, 1999, and 1998. Lines were drawn to encompass the higher EAB density zones, the mortality estimates, and the nearby new finds for each year. For 2002 and 2003, we used the pest maps from Michigan DNR mentioned above. Although EAB probably entered the United States prior to 1998 and was likely present in these trees prior to that date, we started with 1998 as the first year to estimate the visual damage front based primarily on the Smitley (2005) data. These

data indicated that ash tree mortality was already quite high in that zone by 2003, which coincided with our assumption that it takes about 6 years for a cell to reach peak infestation (see "Gravity Model Scenarios"). Subsequent studies of tree rings in the initial zone of infestation have indicated that initial death of ash trees occurred in 1997 (Nathan Siegert. Personal communication, 2006. Department of Forestry, Michigan State University, East Lansing, MI 48824). The final map shows estimated limits of the front by year for 1998–2005.

Modeling Spread in Ohio

Most of the data collected in the preceding sections was a prerequisite for efforts to model the spread of the EAB. We have worked some years on a SHIFT model, designed to estimate the potential migration of trees under the northward climatic pressure (Iverson and others 1999, 2004a, 2004b; Schwartz and others 2001). This model was adapted to work for the spread of EAB. The fundamental basis of this model is a spread model that is driven by existing local density of infestations, ash BA, and the distance of habitat patches to known and modeled infestations. This basic model required modification based on the idea that EAB spread is facilitated through human activities (insect-ride model).

The formula SHIFT uses to calculate the probability of an unoccupied cell becoming colonized during each generation is:

$$P_{colonization,\ i} = HQ_i\ (\ \Sigma\ HQ_j \times F_j \times (C/D_{i,j}{}^{x}))$$

where $P_{colonization,\ i}$ is the probability of unoccupied cell i being colonized by at least one individual and surviving into reproductive status; HQ_i and HQ_j are habitat quality scalars for unoccupied cell i and occupied cell j, respectively, that are based on the basal area of ash in each 270-m cell; F_j, an abundance scalar (0 to 1), is related to the current estimated abundance of EAB in the occupied cell j; and $D_{i,j}$ is the distance between unoccupied cell i and an occupied cell j.

The colonization probability for each unoccupied cell, a value between 0 and 1, is summed across all occupied cells at each generation. Thus, an unoccupied cell very close to numerous occupied cells may end up with a colonization probability greater than 1.0. These cells are modeled as colonized. For cells with summed colonization probabilities less than one, a random number less than 1.0 is chosen, and all cells with a probability of colonization that exceeds the random number are colonized in that model step. Those "newly colonized" cells then contribute to the colonization probability of unoccupied cells in the next model time step. The value of C, a rate constant, is derived independently through trial runs to achieve a migration rate of approximately 20 km per year under high ash BA and moderate EAB abundance. The value of X, or dispersal exponent, determines the rate at which dispersal declines with distance. Being in the denominator, this decreases colonization with distance as an inverse power function. Further discussion on the dispersal function can be found in Schwartz and others (2001).

Insect-Flight Model—

With the insect-flight model, we use the modified SHIFT model to advance the front based on the current front location, the abundance of EAB behind the front, and the quantity of ash ahead of the front. The model runs at a 270-m cell size, and based on the known progression of EAB densities and ash mortality in outlier zones, we assume an 11-year cycle for EAB initial infestation to death of all ash trees in the cell. EAB abundance in the cell was assumed to form a modified bell-shaped curve, with maximum abundance (multiplier = 1) in years 6, 7, and 8; a 0.6 multiplier in years 5 and 9; a 0.14 multiplier in year 4; a 0.011 multiplier in year 3; a 0.0003 multiplier in years 2 and 10; and a 0.0001 multiplier in years 1 and 11. The assumptions for this curve include a slow EAB population increase for the first few years after colonization, followed by peak infestation for 3 years starting with year 6, followed by a rapid decline as all the ash trees in the cell die off in years 9 to 11. The fine-scale ash BA for Ohio was normalized to 0 to 100 and also used as a multiplier. The 11-year cycle may be a liberal assumption on how fast the EAB infestations can grow, as there is some evidence that it may take as long as 10 years for populations to peak (rather than the 6 we assumed). For each cell, the program calculates the probability of new colonization, based on a small probability that the insect

will fly from an occupied cell to an unoccupied cell, for all surrounding cells within a specified search window (40 km in this case). Once selected for colonization, the cell starts the 11-year cycle of EAB increasing and then decreasing as ash dies out.

Insect-Ride Model—

To develop the insect-ride model, we used GIS data to weight factors related to potential human-assisted movements of EAB-infested ash wood or just hitchhiking insects: roads, urban areas, various wood products industries, population density, and campgrounds. Each of these five factors was converted into weighting layers that became multipliers for the ash BA component of the insect-ride model. That is, the increase in probability of EAB infestation by the insect-ride factors is made manifest by increasing the amount of ash available in those cells. Thus, if no ash exists in the cell, it matters not whether there is an escaped EAB from one of the human-assisted vectors, but if there is a large ash component, an escaped EAB could quickly find a place to colonize.

To register the increased probability of insects riding on windshields, radiators, or otherwise attached to vehicles moving down the road, we assigned weights to two widths of major road corridors. We used the U.S. Geological Survey major roads data and created buffers of 1 and 2 km, with a scoring of 10 for 0 to 1 km and 5 for 1 to 2 km distance from the roads.

For urban areas, where there is much more vehicular density and opportunity for EAB transport, we assigned values of 7 if the urban center size was less than the median size and 10 if greater than the median. We therefore assume larger cities will have greater chance of EAB infestation via human movement. Data were acquired for the State of Ohio urban centers from the Department of Transportation Office of Technical Services (Ohio Department of Transportation 2006).

Related to the urban areas, weighting is the population density scoring by zip code. This factor creates a wall-to-wall scoring and distinguishes rural from more urbanized areas. Data were acquired from the U.S. Census Bureau, which included population estimates for 2001 by zip code area. Population densities were divided into six classes with scoring as follows: 1 = 1 to 100 people/km^2; 2 = 101 to 200; 4 = 201 to 800; 6 = 801 to 2,000; 8 = 2,001 to 4,000; 10 = 4,001 to 16,582.

Wood products industries also have been responsible for some EAB movement, so a scheme was developed to weight buffers around individual businesses dealing in wood products. We performed an analysis of potential industries carrying wood products, based on the listing of SIC codes from Dunn and Bradstreet. We scored each industry for likelihood of EAB getting to the site and emerging based on our estimate of the amount and status of ash used in the industry: 0 = none; 2 = small likelihood; 4 = somewhat likely; 6 = higher likelihood. For example, forest nurseries and wood pallet industries scored a 6, whereas manufacturers of decorative woodwork or wooden desks scored a 4 (mostly used kiln-dried wood), and manufacturers of pressed logs of sawdust or woodchips scored a 2. Movement of material from nurseries historically has been a source for several infestations, which are not accounted for in this model. Presumably, this source has been slowed recently via quarantine regulation. Next, buffer distances around the businesses were created based on the number of employees (surrogate for size or volume of wood) working at the facility. For 1 to 10 employees, the buffer of 0 to 1 km scored 8, and the 1 to 2 km buffer scored 3; for 11 to 50 employees, the buffer of 0 to 1.5 km scored 9, and the 1.5 to 3 km buffer scored 4; and if the facility had more than 50 employees, the 0 to 2 km buffer scored 10, and the 2 to 4 km buffer scored 5. Because facilities could be within each other's buffer space, scores were added, and the maximum score over the study area was 22.

Finally, campgrounds were considered likely destinations of human-assisted EAB transport, primarily through the (mostly illegal) movement of firewood. The general public is the primary vector, so it is much more difficult (relative to industry vectors) to achieve education, regulation, and enforcement goals related to stopping EAB spread. Campgrounds were treated in two ways: through the weighting scheme described here and the gravity model described in the next section. Campground locations were acquired from Dunn & Bradstreet (unpublished data

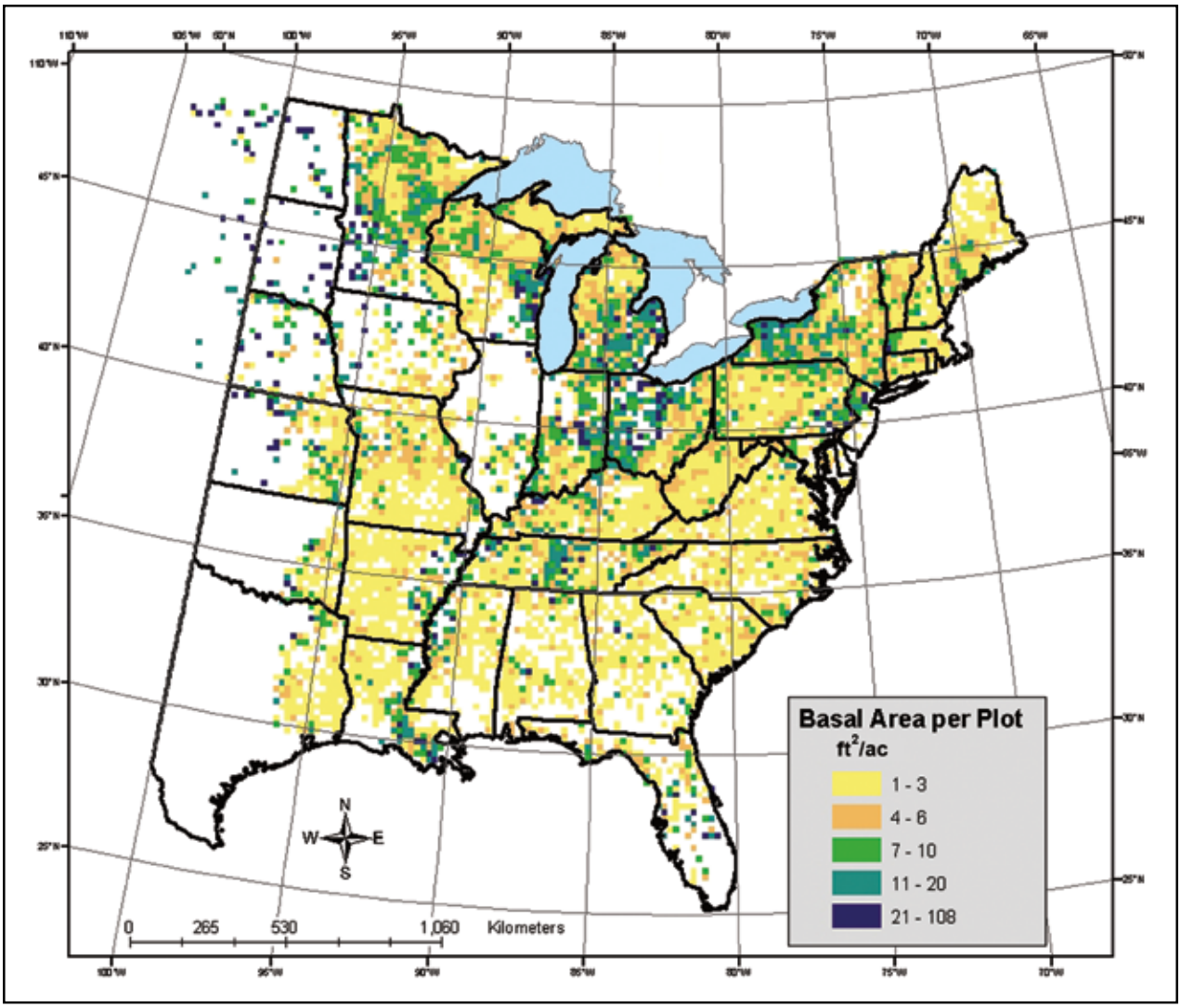

Figure 1—Ash basal area (square feet per acre for 20- by 20-km cells) across the Eastern United States, from Forest Inventory and Analysis data for white, green, black, and blue ash.

purchased by Iverson) and the AAA Travel and Insurance Company (unpublished data provided to Bossenbroek). Similar to that described for wood products industries, we base the weighting on both distance (from the camp headquarters) and number of campsites. For campgrounds with less than 50 campsites, the buffer of 0 to 0.5 km scored 10, and the buffer of 0.5 to 1 km scored 5; for 51 to 200 campsites, the equivalent buffers were 0 to 1 (10 points) and 1 to 2 km (5 points); for 201 to 400 campsites, buffers were 0 to 1.5 and 1.5 to 3 km; for 401 to 600 campsites, buffers were 0 to 2 km and 2 to 4 km; and for more than 600 campsites, buffers were 0 to 2.5 km and 2.5 to 5 km.

Gravity Model Scenarios—

In the second approach used with campgrounds, we are developing a gravity model (Bossenbroek and others 2001) that considers traffic volumes and routes between EAB source areas and various distances to campgrounds (Muirhead and others 2006). Muirhead and others (2006) presented an initial model predicting human-mediated dispersal of the EAB through the movement of campfire wood. Given the rapid spread of the EAB and a need for a quick response, simple models based on simple assumptions, such as developed by Muirhead and others (2006), are an essential step. One of the goals of this project is to incorporate

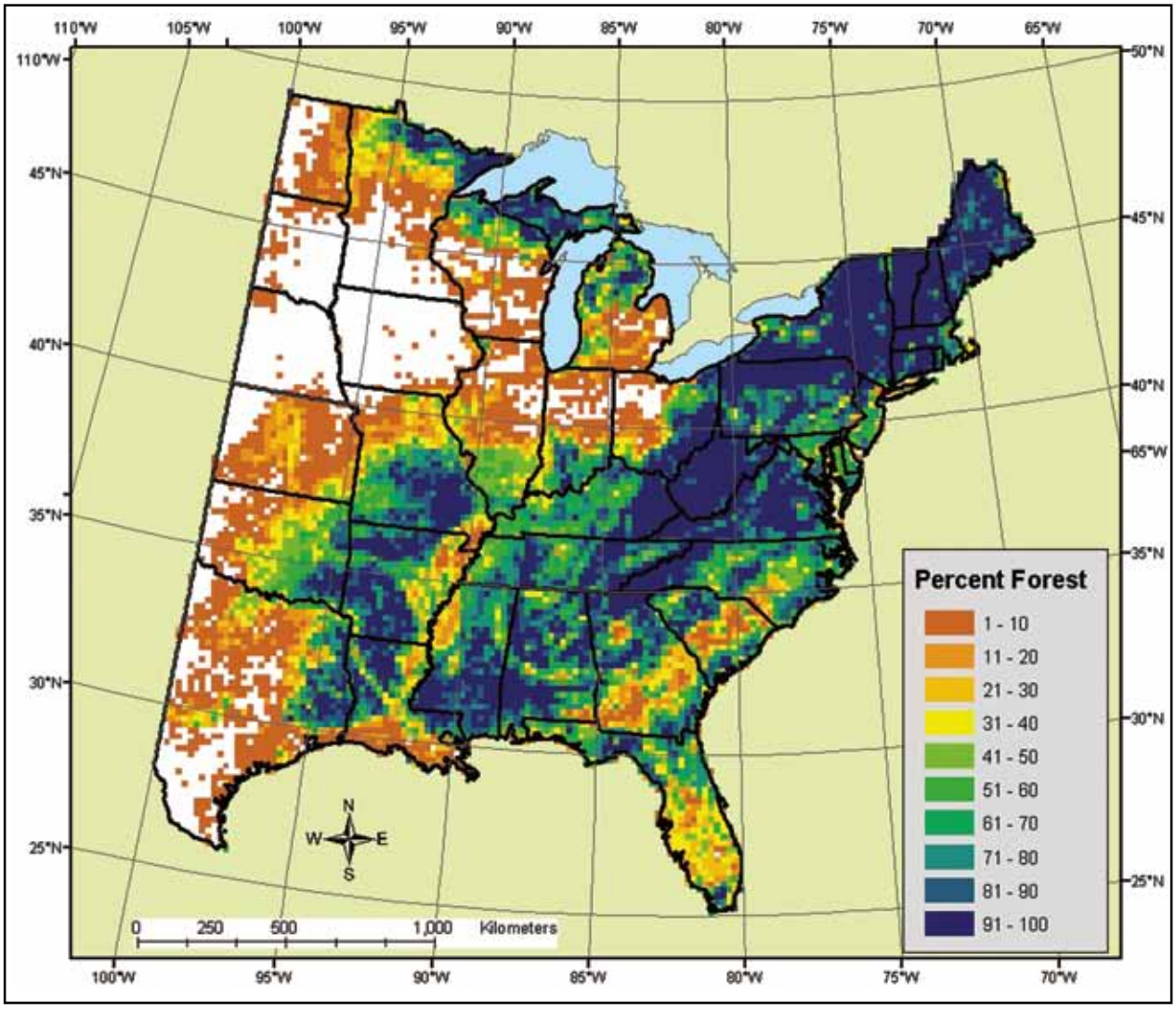

Figure 2—Percentage of forest cover per 20- by 20-km cell, based on the forest/nonforest classification of all the classified 30-m pixels within each cell.

more detail into the models of long-distance dispersal of the EAB. Empirical data on the use of campgrounds, i.e., reservation data, is only available for public campgrounds; thus to incorporate private campgrounds, a modeling framework is necessary. Here we develop a gravity model for Ohio to predict the relative number of campers traveling from EAB infested areas to the campgrounds of Ohio.

Gravity models calculate the number of individuals, (e.g., campers) who travel from location i to destination j, (e.g., a campground), T_{ij}, as estimated as

$$T_{ij} = A_i O_i W_i c_y \quad (1)$$

where, Ai is a scalar for location i (see below), O_i is the number of people at location i, W_j is the attractiveness of location j, c_{ij} is the distance from location i to location j, and α is a distance coefficient, or distance-decay parameter, which defines how much of a deterrent distance is to interaction. A_i is estimated via

$$A_i = 1 / \sum^{N}_{j=1} W_i c_y , \quad (2)$$

where N represents the total number of destinations, and j represents each destination in the study region. A production-constrained gravity model of the movement of firewood thus requires information on the number of campers,

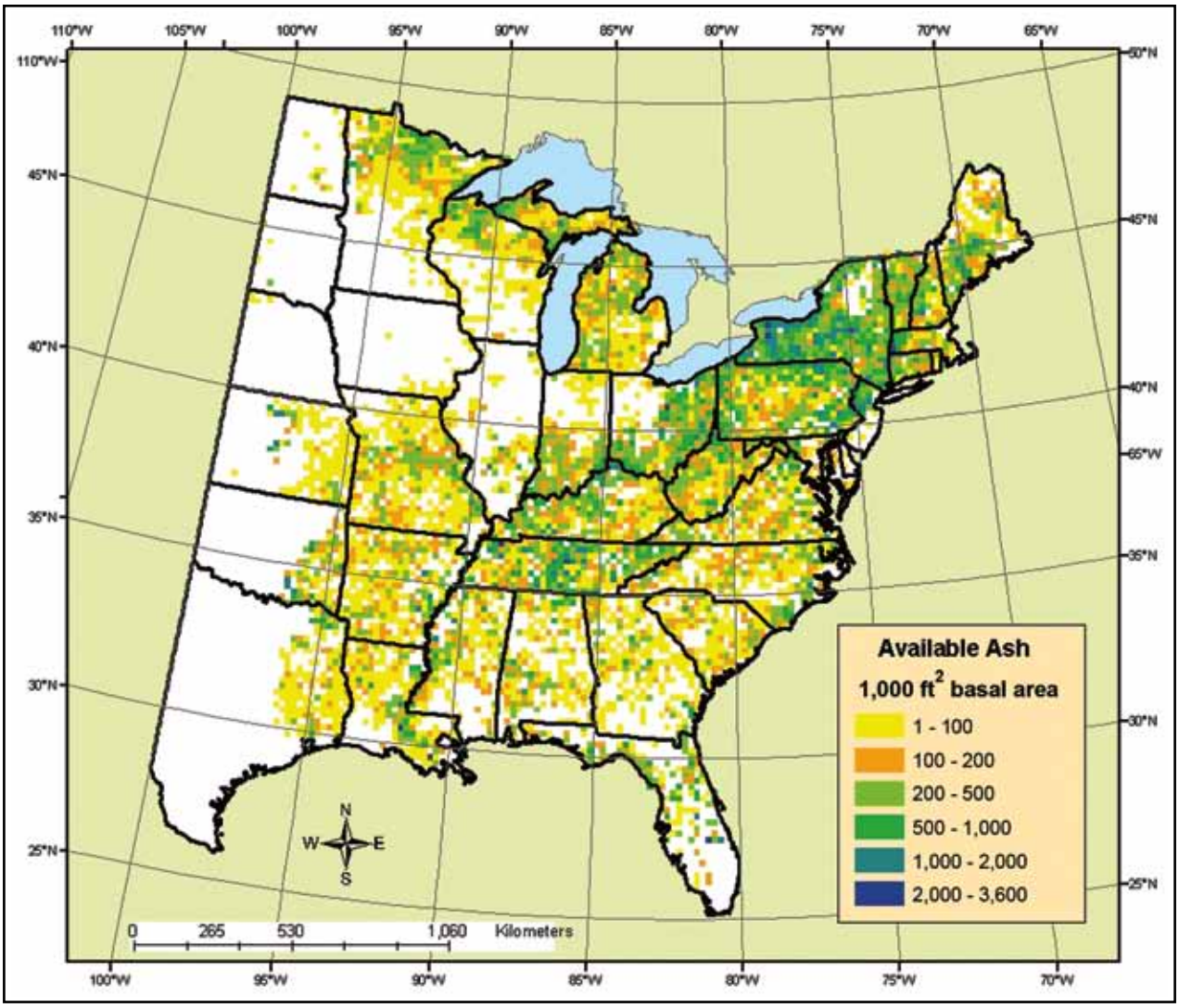

Figure 3—Amount of ash available (square foot basal area of ash per 20- by 20-km cell) to the emerald ash borer. It is the product of Figures 1 (basal area of ash) and 2 (percent forest).

the residency of the campers, the location of potential destinations (i.e., campgrounds), the attractiveness of those destinations, and the distribution of the EAB (i.e., source locations). The spatial resolution of our gravity model is based on ZIP code regions for the residency of campers and the point locations of campgrounds.

Based on data from Dunn & Bradstreet and the AAA Travel and Insurance Company, we identified the location of 241 public and private campgrounds in Ohio. For a measure of attractiveness for each campground (w) we initially are using the number of camp sites at each location. Other factors, such as proximity to boating, fishing, and hiking, are likely to influence the attractiveness of individual campgrounds, but these data are unavailable on a regional and consistent basis. The distance between a ZIP code and a campground (c) was calculated as the road network distance between these locations. For simplification, the road network is based on all roads with either a State or Federal designation and excludes local roads. The point of origin for each ZIP code was determined as the road location nearest the centroid of the ZIP code region. Likewise, for each campground, the point location was determined as the point on the nearest road to the campground. The result of the gravity model is a prediction of the number of campers that

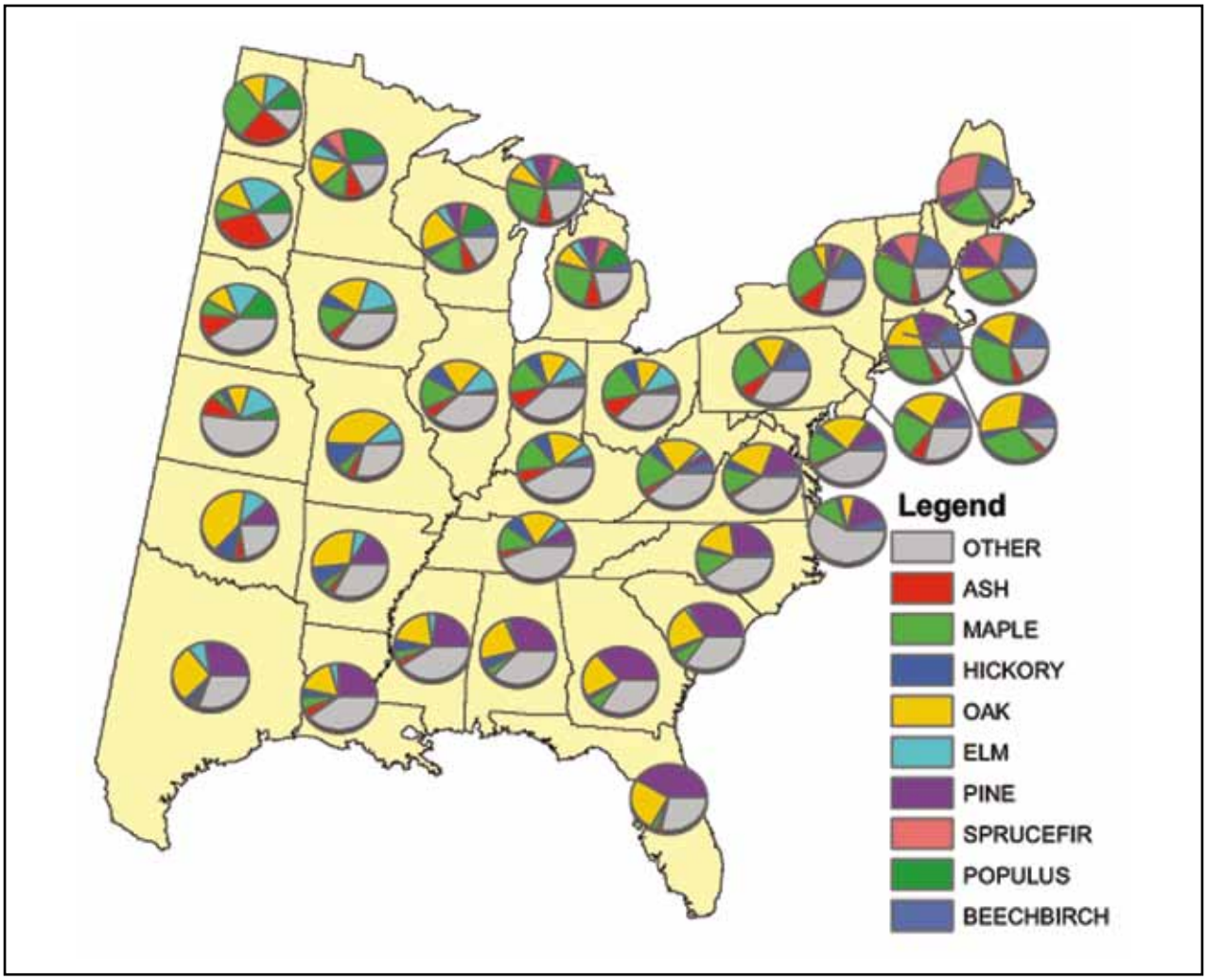

Figure 4—Proportion of various genera of trees, based on basal area as calculated from data depicted in Figure 3. The proportions of ash are highest in the Northern States.

travel from an area of EAB infestation to each particular campground.

To estimate the distance coefficient (α), we compared our gravity model with reservation data obtained from the Ohio Division of Parks and Recreation for 58 state parks. These records contained the number of reservations for each campground summed by ZIP code of the camper's residence. We used sum of squares to measure goodness-of-fit between model predictions and the observed data. To identify the best-fit model, the value of α was systematically assessed over a range from 0.1 to 10. By fitting the model to the reservation data for Ohio state parks, we assume that campers using private and public campgrounds behave in the same manner, i.e., distance and attraction affect their travel decisions in the same manner.

Once the gravity model was parameterized, we used the estimated distance coefficient value to determine the expected number of campers that would travel to all 241 campgrounds within Ohio. We reported the percentage of campers coming from EAB-infested ZIP codes (as of 2003) traveling to each campground in Ohio to give a relative estimate of risk.

Results and Discussion

This project is a work in progress, and consequently, results presented in sections 3.1 and 3.2 could change pending new

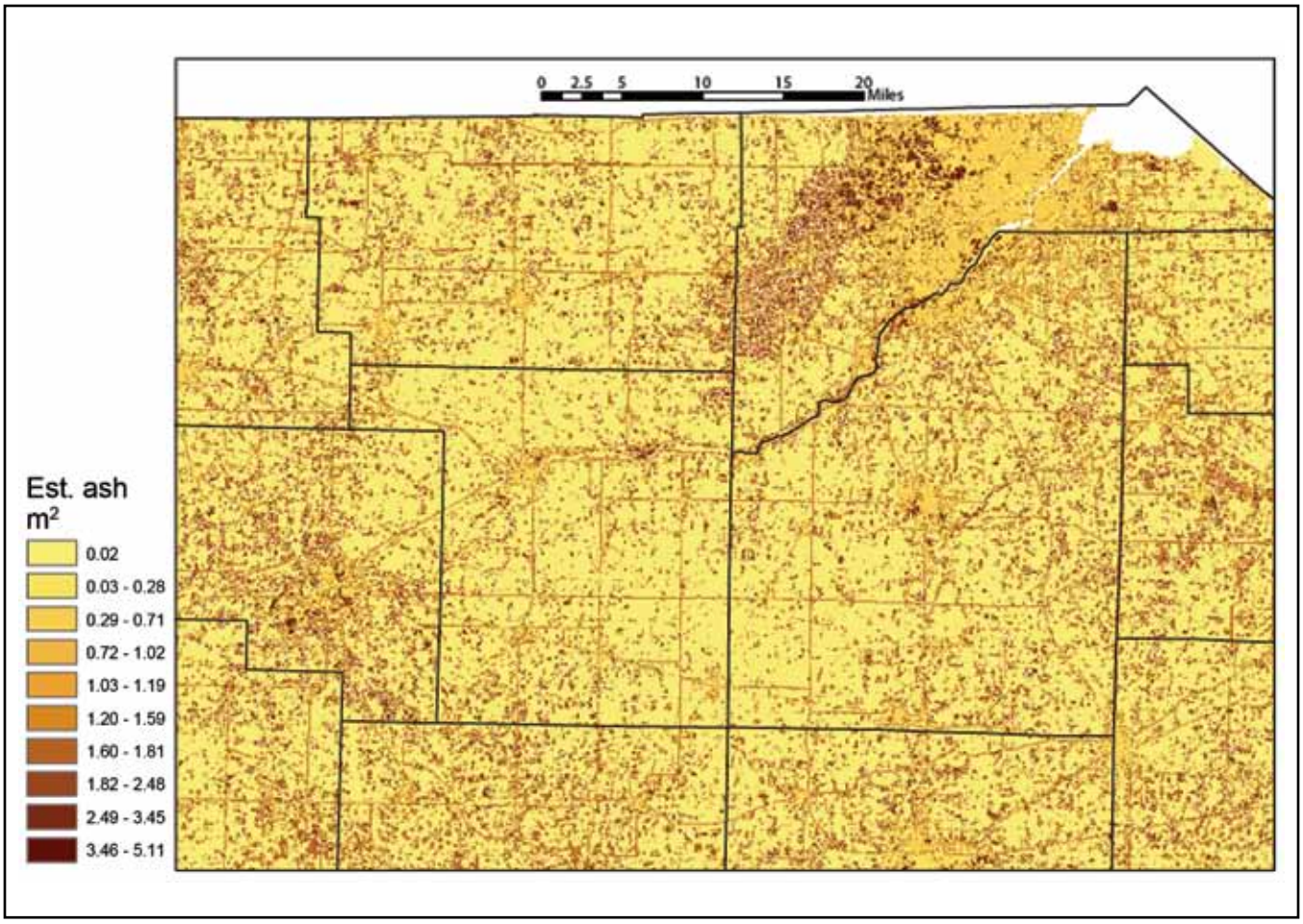

Figure 5—Estimated distribution of ash for a portion of northwest Ohio, calculated at a resolution of 270 m (but not resolved that finely for this map). Data are based on classified 30-m Landsat imagery and Forest Inventory and Analysis plot data for the entire State.

data or analysis or both. Results reported in "Modeling Spread in Ohio" are very preliminary.

Distribution of Ash

Analysis of the distribution of ash at two scales showed two facts: there is a lot of ash available to the insect, and it is distributed throughout the Eastern United States. Consequently, the EAB threat is real for most communities and rural locations throughout the region.

Coarse-Level Analysis of Ash for Eastern United States—

The map of ash BA (including white, green, black, and blue ash) per unit area of forest shows there is a great deal of ash in the woodlots and small forests common within the current range of the EAB (southern Michigan, northern Ohio, northeastern Indiana) (Figure 1). However, the amount of forest in that zone is limited (Figure 2), so the total available ash is less compared to the more forested regions (Figure 3). Of major concern is the large amount of ash available just south of Lake Erie (northeast Ohio, northwest Pennsylvania) and Lake Huron (western New York). The western edge of this zone is just now being reached by the EAB.

These maps show a high level of ash availability in the zones surrounding the borer's current range, indicating a difficult control task ahead.

Figure 4 shows a map with the proportions of various genera of trees in each State of the Eastern United States. Ash comprises a significant proportion of basal area across the Northern States, but is less prevalent in the Southeastern States.

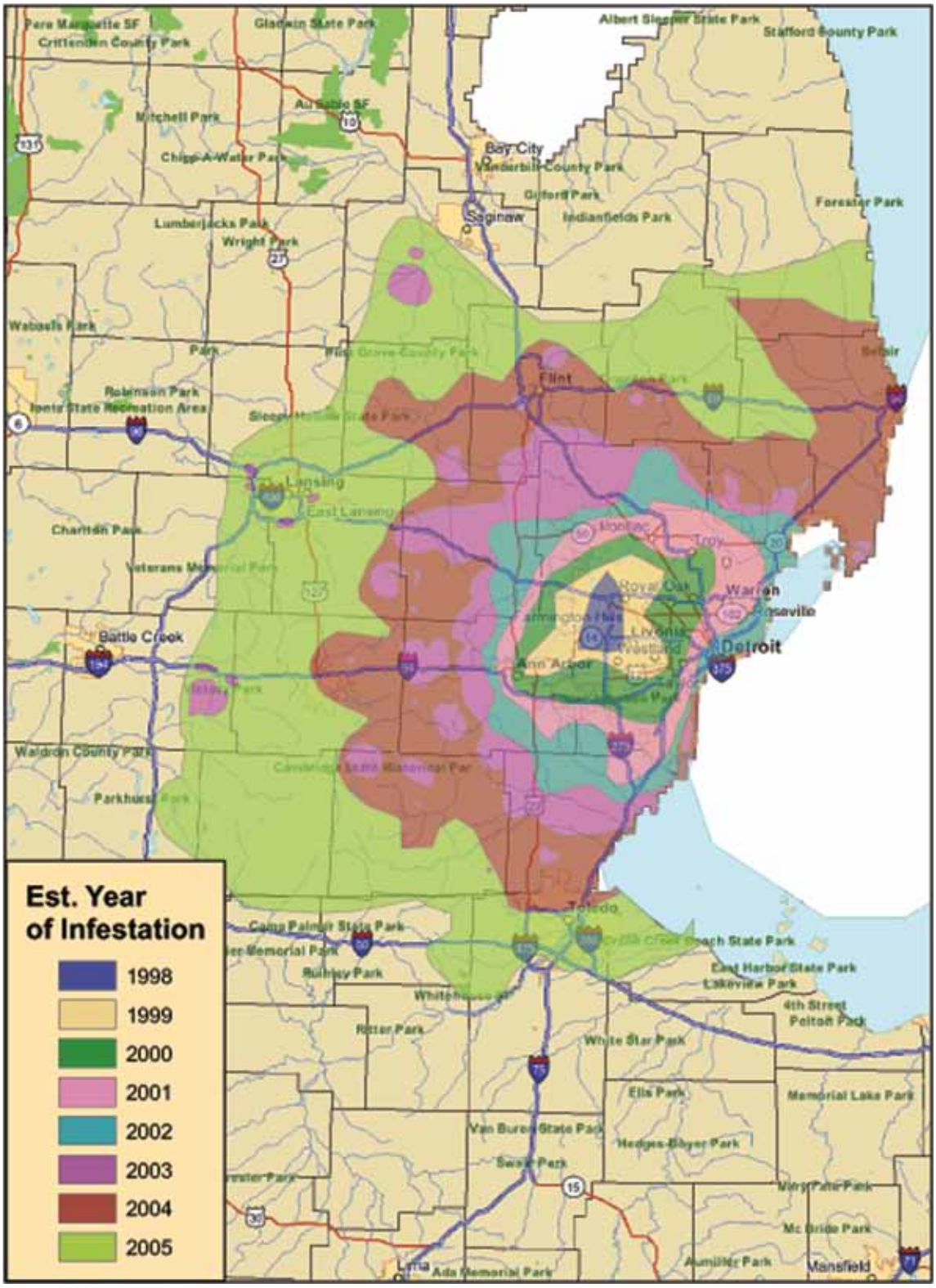

Figure 6—Estimated emerald ash borer front spread by year, 1998-2005, as estimated from a variety of data.

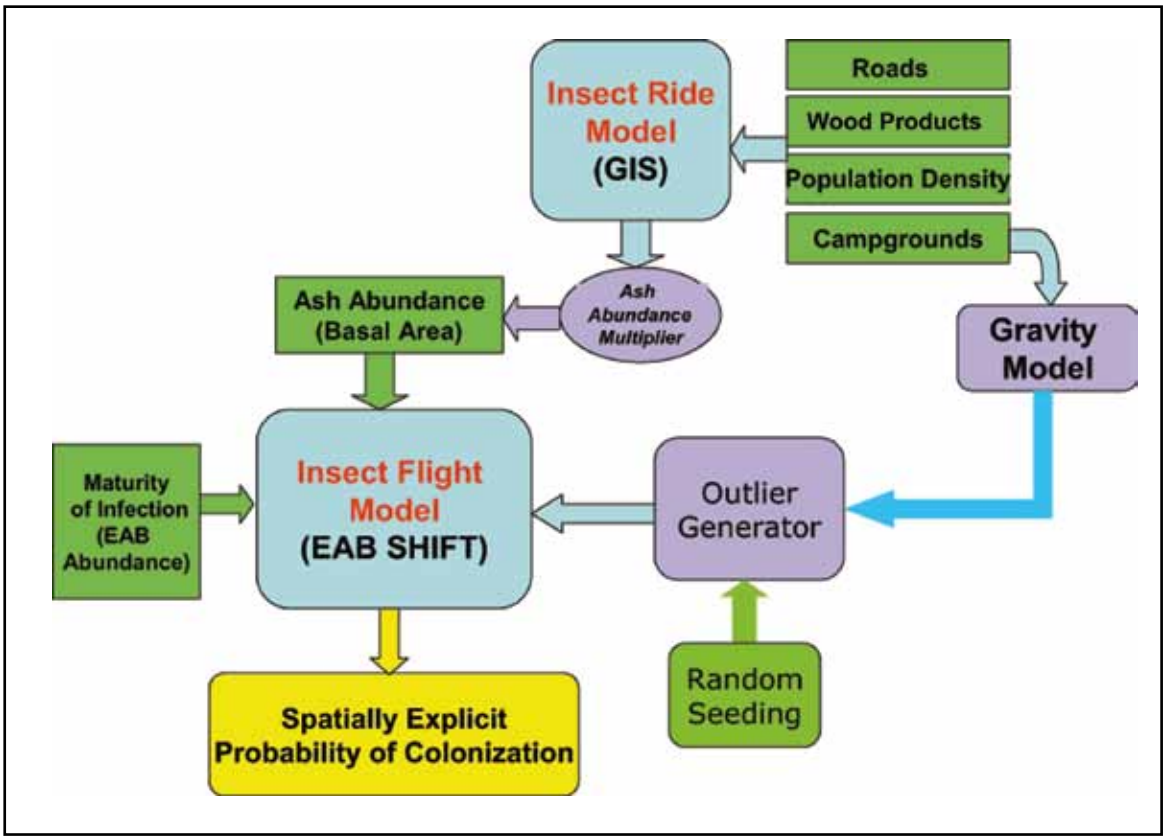

Figure 7—Modeling framework showing two major components–the insect flight and insect ride models. The insect ride model considers both a geographic information system weighting scheme and the gravity model of attractiveness of campgrounds for receiving emerald ash borer (EAB) from the core zone in southern Michigan. The insect flight model considers the observed rate of spread of 20 km/yr, the emeral ash borer (EAB) abundance, and the abundance of food for EAB.

Fine-Scale Analysis of Ash for Ohio—
The fine-scale analysis for Ohio, using 30-m data and plot information, shows an estimate of the urban and riparian zones with levels of ash (BA) (Figure 5). Most of the area shown in Figure 5 is agricultural land, but ash is maintained in the landscape even in these croplands along roadsides, ditches, and small wetlands. There are also numerous woodlots, many of which contain high proportions of ash.

Mapping Estimated EAB Spread, 1998–2005

The map of estimated EAB front locations was required for two reasons: (1) to create a baseline from which our spread modeling will commence; and (2) to estimate the average historical rate of spread that will help calibrate the model. The resulting map (Figure 6) shows expansion from a core area in western Detroit, with substantial concentric movement each year. Using these data, and assuming a start date of 1998, we calculated an average spread rate of approximately 20 km/yr for the years 1998 through 2005. This expansion rate is much faster than the field and laboratory dispersal (flight) studies that have been presented thus far of 1 km/yr (McCullough and others 2005) to 4.8 km/yr (Taylor and others 2005), respectively. Clearly, much of the historical movement of the front, as we detected it here, is hastened by shorter human-assisted movements, and the two mechanisms (flight vs. ride) cannot be clearly distinguished from each other in the real world.

Modeling Spread in Ohio

We present a modeling framework that considers both the insect- and the human-controlled dispersal mechanisms (Figure 7). Though we have not completed this work, we have some preliminary results, which are presented here.

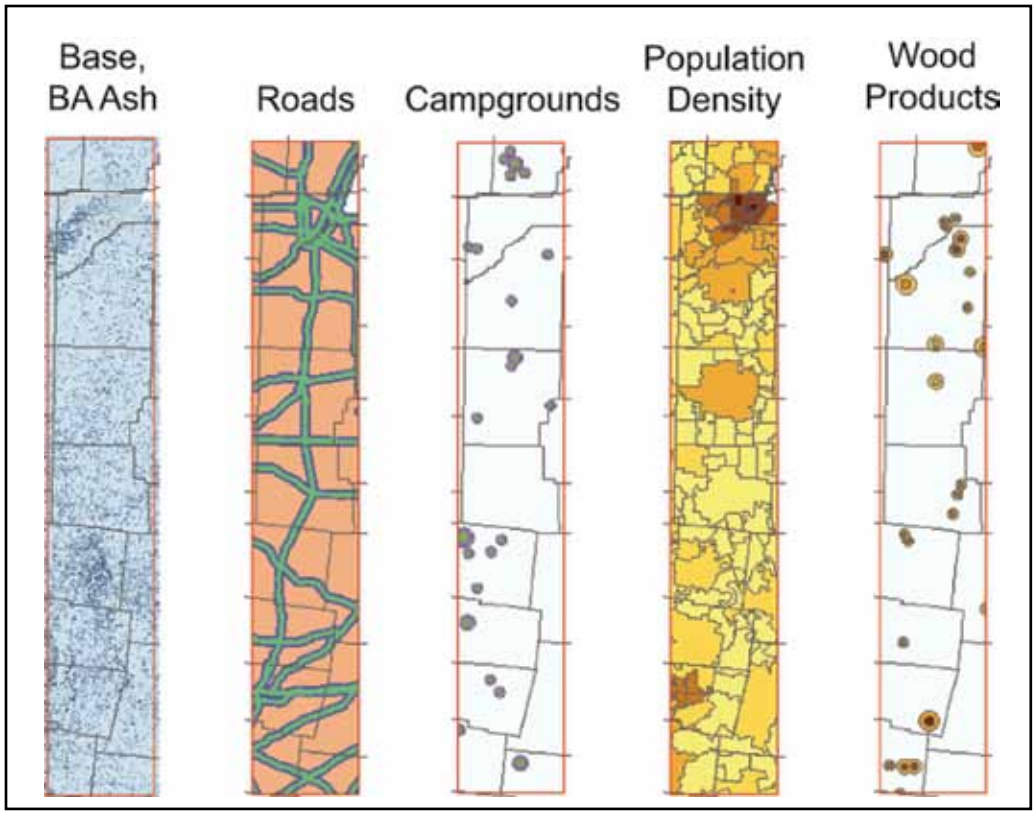

Figure 8—Insect-ride components. Small map strips of Ohio stretching south from Toledo to Columbus, showing more detail of relative weights of the area for basal area of ash, roads, campgrounds, population density, and wood products industries.

Insect-Ride Model—

When we include the five factors of human-assisted dispersal, all of the land is affected to some degree (Figure 8). These factors together modify the environment for susceptibility for EAB invasion in our model by supplying a multiplier to the quantity of ash available to the EAB. In our example section of Ohio, we see that the largest multipliers will be in the densely populated centers, especially where there are wood products industries and roads nearby. We have yet to experiment with various weighting schemes among the five factors. For example, we plan to incorporate relatively more influence of campgrounds, probably via the gravity model.

Gravity Model—

In evaluating Ohio campgrounds, we demonstrate the influence of proximity to the core area of EAB presence. Figure 9 shows that the higher scores (larger symbols) are at campgrounds with more campsites (=more attractiveness), with more traffic, and that are closer to the core area of EAB infestation in southern Michigan. The areas around these larger symbols are potential areas that should be monitored with detection trees and visual inspections, as new outliers may emerge near these zones.

Insect-Flight Model—

The EAB Shift model produces an estimate of relative probability of colonization away from the already occupied zones. Figure 10 shows the preliminary results of a test strip from Toledo to Columbus, Ohio (same strip as shown in Figure 8). The relative probability of colonization decreases quickly from the EAB range boundary edge (Figure 10, top strip). When we add the influence of single factor weights (e.g., roads, campgrounds, population density, and wood products industries), there are some minor variations that align with the weights in the preliminary output (Figure 10). We emphasize that this example is only to show the kinds of outputs we are pursuing and that the testing and calibration

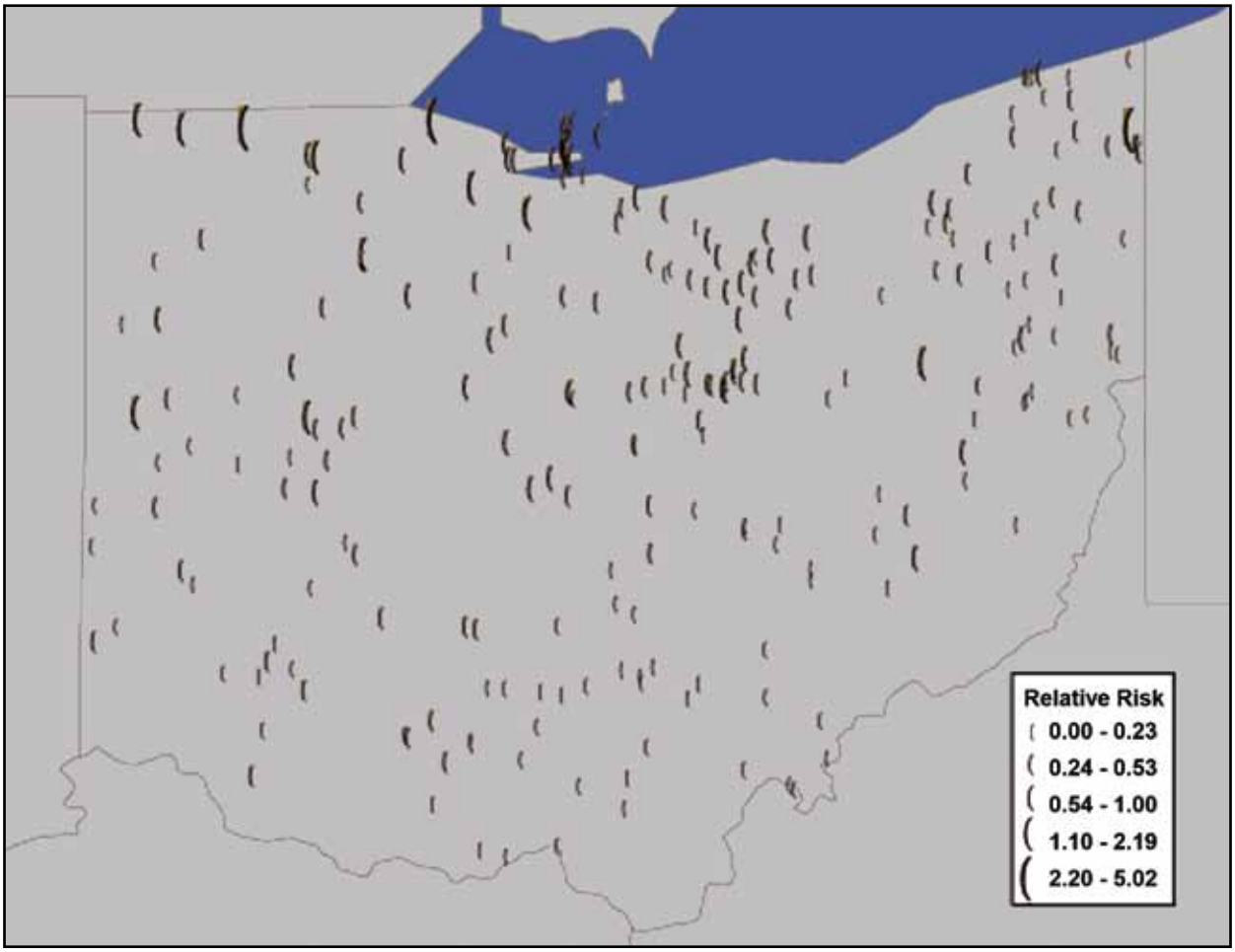

Figure 9—Ohio campground scores with gravity model. Larger marks represent increasingly higher scores of relative potential for emerald ash borer (EAB) invasion owing to higher attractiveness or travel or both from the EAB-infested core area in southern Michigan.

is still in progress. We also have begun to incorporate an outlier seed generator, which depends partly on a random generator and partly on the weighting scheme of the insect-ride components.

Conclusions

The results on assessment of the ash resource, estimates of past spread of EAB, and preliminary efforts to create a model of spread leave us with the following conclusions:

- There is a great deal of ash resource in the Eastern United States, especially in the northern half of the region. For many States, ash makes up a sizeable portion of the total BA.
- As of spring 2006, the front border of the current EAB infestation is just now reaching the areas with the largest amount of available ash, e.g., in northeast Ohio, northwest Pennsylvania, and western New York.
- Although much of the current expanding range of EAB in northwest Ohio and northeast Indiana is dominated by agriculture, our high-resolution analysis shows plenty of ash exists for EAB expansion in this zone in small woodlots, riparian woods, small wetlands, and miscellaneous parcels bordering the agricultural fields.
- The map of our estimate of the expansion of the front from 1998 to 2005 shows a fairly consistent pattern of roughly 20 km/yr. This rate

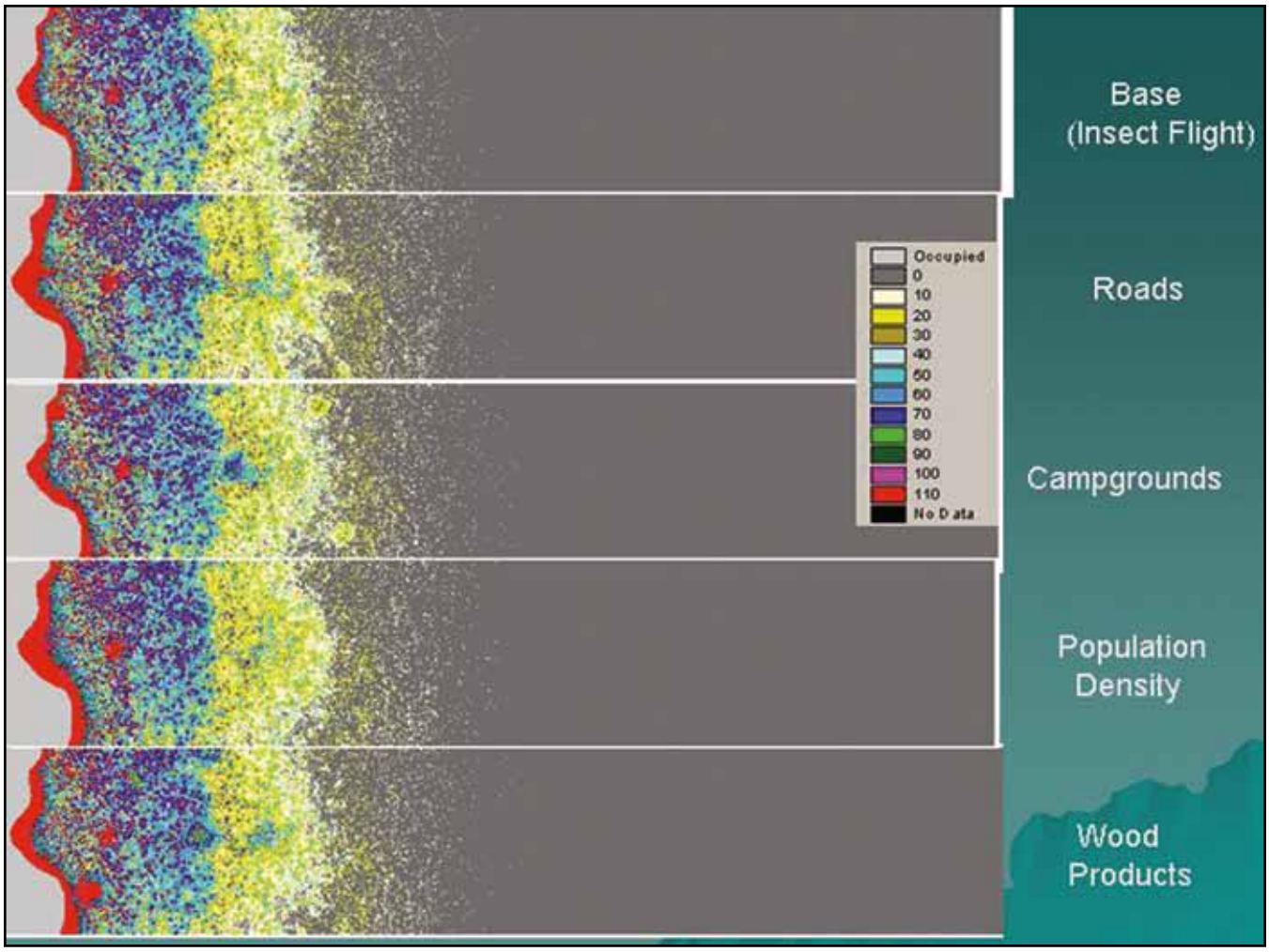

Figure 10—Combined model outputs using single-factor weights. These maps show preliminary results on the Toledo (left side) to Columbus (right side) test strip of the emerald ash borer Shift base run, and then with single-factor multipliers for roads, campgrounds, population density, and wood products industries. Numbers correspond to relative colonization probabilities after 11 years of runs. It does not include random or directed outlier generation that may occur through the insect-ride or gravity modeling components.

of expansion would necessarily have to include both the biological dispersal capacity of the insect and some short-distance movement assisted by humans (e.g., on or in vehicles, plant material, wood material, etc.).

- The components of the insect-ride model (roads, campgrounds, wood products industries, population density, and urban centers) have been acquired and processed to create a weighting scheme based on various factors, including buffer distances and number of people involved in the endeavor. When combined, every 270-m pixel in the study area has been scored for its likelihood of enhancing EAB spread.
- The gravity model yielded a relative scoring of potential EAB invasion among campgrounds based on traffic from the core EAB zone and attractiveness of the campgrounds.
- Preliminary test results of movement of the front from the EAB shift model shows the probability of colonization diminishes quickly away from the front, and that the insect-ride components modify those results through the multiplier effects.

- We hope to use these data along with GIS and modeling tools to better understand the potential rate of spread, which could inform management decisions that will hopefully slow the spread of this destructive pest.

Acknowledgments

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Risk Analysis and Guidelines for Harvest Activities in Wisconsin Oak Timberlands to Minimize Oak Wilt Threat

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Abstract

Oaks (*Quercus* spp.) are an important species group in the forests of Wisconsin. The State's timberland typed as oak-hickory forest was estimated at 2.9 million acres in 1996. Growing stock volume for red oak was estimated at 2.4 billion cubic feet, whereas select white oak volume was estimated to be 927 million cubic feet. Oak wilt, the oak disease of greatest concern in Wisconsin, is widespread in the lower two-thirds of the State. Harvest activities in oak stands may result in introduction of the disease agent, *Ceratocystis fagacearum* (Bretz), into the stand or promote intensification of the disease within the stands or both. A risk-rating system based on scientific- and experience-based knowledge was used to develop a statewide system for oak wilt risk analysis. Guidelines for timber harvest activities in oak stands were then developed based on results of the risk analysis. The analysis and recommendations have been published (http://www.dnr.wi.gov/forestry/fh/oakWilt/guidelines.asp [Date accessed: July 8, 2010]) in three different formats. The formats include a pdf version of decision-trees with accompanying tables, a simple spreadsheet application allowing the user to obtain specific guidelines based on his/her response to five questions about the stand and timing under consideration, and an interactive online format derived from the spreadsheet version. The query page of the interactive formats is linked to a concealed table containing the risk analysis and recommendation matrix. The tool provides consistent, statewide guidelines for harvest activities that will, when applied, minimize spread and reduce the biological and economic impacts of oak wilt to Wisconsin's oak timberlands. The rule-based, expert-driven system approach used to develop these guidelines could be used to assess risk and develop large-scale management guidelines for other established forest pathogens.

Keywords: *Ceratocystis fagacearum*, oak wilt, *Quercus* spp., risk analysis, timber harvest guidelines.

Introduction

Oak Forests of Wisconsin

Oaks (*Quercus* spp.) are a dominant component of the extensive oak-hickory forests of the Central U.S.A. (Leopold and others 1998). In Wisconsin, timberland typed as oak-hickory forest was estimated at 2.9 million acres in 1996 (Schmidt 1997). Growing stock volume for red oak (section Lobatae) was estimated at 2.4 billion cubic feet, whereas white oak (section Quercus) volume was estimated to be 927 million cubic feet (Schmidt 1997).

Oak Wilt – Primary Disease of Concern

Oak wilt, the oak disease of greatest concern in Wisconsin, occurs in 51 of the State's 70 counties (http://www.na.fs.fed.us/fhp/ow/maps/ow_dist_fs.shtm [Date accessed: July 8, 2010]). Thousands of oaks in woodland and urban settings succumb to the disease every year. The causal fungus, *Ceratocystis fagacearum* (Bretz), is spread from diseased to healthy oaks belowground through functional root grafts or aboveground by insect vectors (Tainter and Baker 1996). Species of the sap beetle family (Coleoptera: Nitidulidae) are considered the primary vectors in Wisconsin. New disease centers are established when *C. fagacearum*-contaminated beetles visit fresh xylem-penetrating wounds (e.g., axe blazes, logging wounds, branch-pruning wounds) on healthy oaks and successfully inoculate them with propagules of the fungus (Gibbs et al. 1980, Juzwik and others 2004). Stump surfaces created by tree felling and wounds to branches, stems, and roots by heavy equipment or adjacent falling trees are avenues for infection during timber stand improvement or harvesting activities. In a timber sale unit near Waube Lake, Wisconsin, many new infection centers occurred over a large area following a May 2001 timber harvest (M. Mielke 2006. Plant pathologist, Northeastern Area State and Private Forestry, USDA Forest Service).

Felling of diseased oaks adjacent to healthy oaks can lead to intensification of the disease within stands if root connections exist. Slow movement of the pathogen through grafted roots of healthy trees felled within 50 feet of a diseased tree explained the sporadic appearance of oak wilt in subsequent years at the edge of clear-felled areas (Yount 1955).

Need for Statewide Guidelines

The Wisconsin Department of Natural Resources (DNR) identified the need to develop consistent, statewide guidelines for timing harvest activities in oak timberland in order to minimize potential for oak wilt introduction or spread or both in existing and future stands where oak regeneration is the management objective. A committee of government, industrial, and consulting foresters was formed to develop such guidelines. Both scientific and experience-based knowledge of the oak wilt host – pathogen system were the basis of the guidelines. The approach used to (1) analyze the risk and the potential for introduction and spread of oak wilt in stands targeted for harvest, and (2) develop guidelines for timing harvest are described in this paper.

Approach

Risk Assessment

Risk refers to the chance of injury or loss defined as a measure of the probability and severity of an adverse effect to health, property, the environment, or other things of value (North American Forest Commission 2004). Our risk analysis includes (1) the assessment of risk posed by the oak wilt pathogen to oak timberland scheduled for harvest and regeneration to oak, and (2) recommendations for minimizing frequency of pathogen introduction to and spread within such stands. A rule-based, expert-driven model, such as that used for pest risk assessment in the Exotic Forest Pests (ExFor) system (North American Forest Commission 2004), was adapted for this analysis. This approach falls under the umbrella term of multicriteria decision analysis, which seeks to take multiple criteria into account when groups explore decisions that matter, e.g., natural resource management decisions (Mendoza and Martin 2006). Two criteria were evaluated within the risk assessment process.

Criterion 1: Risk of *Ceratocystis fagacearum* introduction to the stand [between-stand spread] or for initiation of new centers within the stand [within-stand spread] by insect vectors—
Statements were developed for this criterion that considered two factors: (1) time of year during which harvest activities would occur (resulting in fresh wounds suitable for infection), and (2) proximity of existing oak wilt centers in other locations to the stand in which harvest activities would occur. A risk rating, ranging from very low to very high, was then assigned to each of the possible combinations of time and proximity. The risk values were determined through a group consensus process after review of pertinent scientific literature and of each individual's experience working with the disease.

Criterion 2: Risk of *C. fagacearum* belowground spread within an oak stand following pathogen establishment—
Statements for this criterion included three factors (i.e., stand conditions): (1) density of oaks, (2) general topographic relief, and (3) general soil type in the stand to be harvested. Each of these factors is known, either through scientific studies or experiential knowledge or both, to influence the frequency and the distance over which intraspecific root grafting occurs. Two or more levels were selected for each factor. Basal area (square feet per acre) levels for describing red oak species composition and density were less than 15, between 15 and 35, and greater than 35. The general levels for topographic relief were (a) flat to rolling terrain, and (b) steep hills with deep valleys terrain. Soil type was divided into light textured (sandy, loamy sand, and sandy loam) and heavier textured (all other types depicted in classic soil texture triangle). A risk rating, ranging from very low to very high was then assigned to each of all possible combinations of statements by factor. The risk values were determined by a group consensus process.

Overall risk: combined risk rating for the two criteria—
The ratings for each criterion were then used to generate the overall risk of oak wilt's threat to the stand of interest following a timber harvesting event. The overall rating, ranging from very low to very high, was assigned to each stand scenario based on the combination of introduction and

Table 1—Combined risk ratings for Criterion 1 factors - proximity of oak wilt centers to stand under consideration and proposed timing of harvest activities

Proximity of oak wilt centers to stand of interest			
Within county?[b]	**Within stand?**	**Proposed timing of harvest activities**	**Risk rating[a]**
No	No	Spring to early summer	M
No	No	Summer to early fall	L
No	No	Mid-fall through winter	VL
Yes	No	Spring to early summer	VH
Yes	No	Summer to early fall	M
Yes	No	Mid-fall through winter	VL
Yes	Yes	Spring to early summer	AP
Yes	Yes	Summer to early fall	AP
Yes	Yes	Mid-fall through winter	AP

[a] Explanation of ratings: VH (very high), M (moderate), L (low), VL (very low), AP (oak wilt already present in the stand).
[b] Includes stands occurring in oak-wilt-free counties, but within 6 miles of oak-wilt-affected counties.

root graft spread factors. As before, the risk values were determined through a group consensus process.

Timber Harvesting Guidelines

Timber harvest guidelines for minimizing the initiation of new infection centers and subsequent tree loss from spread within stands were developed based on results of the risk assessment. The risk rating for each stand condition scenario was considered and harvest recommendations determined through a group consensus process.

Display of Risk Analysis Results and Guidelines

Three methods were used to display results of the risk analysis. For the first method, graphical decision-trees were constructed, and associated tables were developed for harvest guidelines for three proximity levels (i.e., no oak wilt in county, oak wilt in county but not in stand, and oak wilt in the stand [not shown]). This output was used in the development of the electronic displays. Initially, the risk analysis and associated harvest guidelines were combined in a simple electronic spreadsheet. The spreadsheet features a front query page that allows the user to obtain risk ratings and recommendations for specific stand scenarios. The query page is linked to a concealed table containing the risk analysis and recommendation matrix. Later, an interactive, Web version of the spreadsheet product was developed for online use.

Results

Risk Analysis Results with Scientific Knowledge Basis

The combined risk ratings for Criterion 1 ("Criterion 1: Risk of *Ceratocystis fagacearum* Introduction to the Stand [Between-Stand Spread] or for Initiation of New Centers within the Stand [Within-Stand Spread] by Insect Vectors") are shown in Table 1. The risk of overland pathogen transmission by sap beetles was considered to increase as proximity to an existing oak wilt center decreased. The existing centers would be the source from which inoculum-laden beetles would originate, assuming oak wilt mats were formed on recently wilted red oaks in that originating center. Menges and Loucks (1984) and Shelstad and others (1991) found higher efficiencies of vector spread over short distances (e.g., ≤ 300 m); longer distance spread occurs very infrequently and on a random basis. Although the number of new centers occurring at greater distances is small, over time they can have a significant influence on distribution of oak wilt within the total forest area (Shelstad and others 1991). Timber harvest activities would result in wounding of residual oaks in shelter wood cut situations or create stump surfaces of removed healthy oaks or both. Such xylem-exposing cuts are attractive to dispersing sap beetles. The risk of pathogen transmission to such wounds by certain sap beetle species is high during the spring months, low from

Table 2—Combined risk ratings for Criterion 2 factors – density of oaks, topographic relief, and general soil type

Density of oaks[a] (ft^2/acre)	Topographic relief	Soil category[b] (texture)	Risk rating[c]
< 15	Flat – rolling	Light	L
15 – 35	Flat – rolling	Light	H
> 35	Flat – rolling	Light	VH
< 15	Flat – rolling	Heavy	L
15 – 35	Flat – rolling	Heavy	M
> 35	Flat – rolling	Heavy	H
< 15	Hills & valleys	Light	L
15 – 35	Hills & valleys	Light	H
> 35	Hills & valleys	Light	H
< 15	Hills & valleys	Heavy	VL
15 – 35	Hills & valleys	Heavy	M
> 35	Hills & valleys	Heavy	M

[a] Density of oaks measured as basal area.
[b] Light texture includes sandy, loamy sand, sandy loam, sandy clay loam, and loam; Heavy texture includes sandy clay, clay, clay loam, silt, silt loam, silty clay loam, and clay loam. Based on classic soil texture triangle.
[c] Explanation of ratings: VH (very high), H (high), M (moderate), L (low), and VL (very low).

Table 3—Stand condition scenarios for which overall risk ratings were high (H) to very high (VH), where oak wilt is not yet present in the stand of interest but occurs elsewhere in the same county or in a second county that is less than 6 miles from the first

Timing for harvest	Oak density[a] (ft^2/acre)	Topographic relief	Soil category[b] (texture)	Overall risk rating
Spring to early summer	>35	Flat - rolling	Light	VH
Spring to early summer	> 35	Hills & valleys	Light	H
Spring to early summer	> 35	Flat - rolling	Heavy	H
Spring to early summer	> 35	Hills & valleys	Heavy	H
Spring to early summer	15 – 35	Flat - rolling	Light	H
Spring to early summer	15 – 35	Hills & valleys	Light	H
Spring to early summer	15 – 35	Flat - rolling	Heavy	H
Spring to early summer	15 – 35	Hills & valleys	Heavy	H

[a] Density of oaks measured as basal area.
[b] Light texture includes sandy, loamy sand, sandy loam, sandy clay loam and loam; heavy texture includes sandy clay, clay, clay loam, silt, silt loam, silty clay loam, and clay loam. Based on classic soil texture triangle.

midsummer to early fall, and none during the late fall and winter (Ambourn and others 2005, French and Juzwik 1999, Juzwik and others 2006).

The combined risk ratings for Criterion 2 ("Criterion 2: Risk of *C. fagacearum* Belowground Spread within an Oak Stand Following Pathogen Establishment") are shown in Table 2. Frequencies of root graft spread increase with increasingly lighter textured soils, e.g., from silt loam to sands (Menges 1978). Furthermore, frequency of root graft transmission is highest for stands with > 60 percent red oak density (Menges and Loucks 1984). Lastly, oak wilt is very common in areas of low topographic relief in portions of Iowa, Michigan, Minnesota, and Wisconsin (e.g., Albers 2001, Menges and Loucks 1984). In areas with obvious

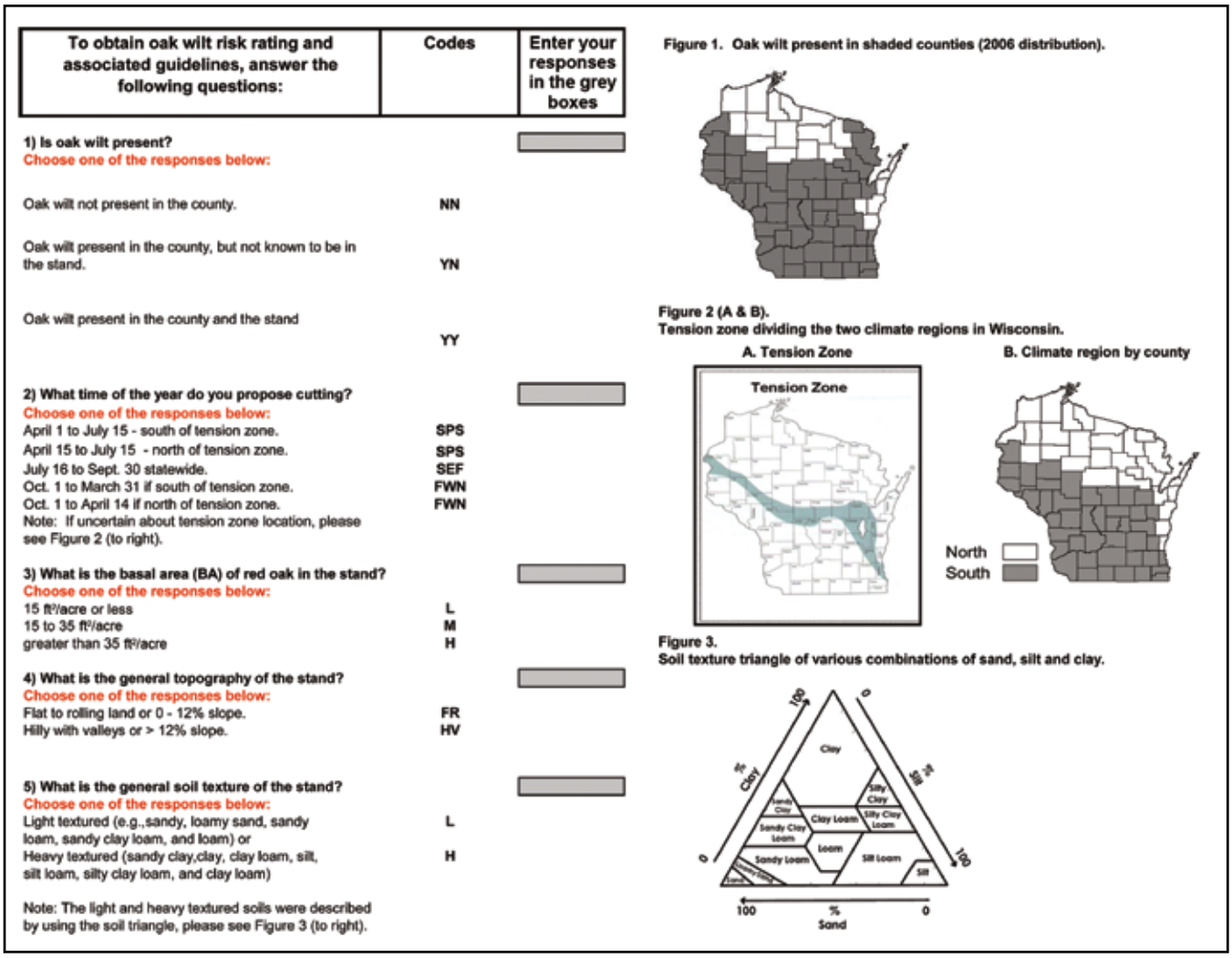
Table 4—Summary of management guidelines for timing of timber harvest activities based on oak wilt risk analysis results

Stand proximity to oak wilt centers	Guidelines by timing of timber harvest activities		
	Spring – early summer	Summer – early fall	Fall – winter
Not in county or within 6 miles of county with oak wilt and not in stand	No restrictions April 1 - July 15 (south)[a] and April 15 - July 15 (north). (12)[b]	No restrictions July 16 - September 30. (12)	No restrictions October 1 - March 31 (south) and April 14 (north). (12)
In county or within 6 miles of a county with oak wilt, but not in stand	May cut between April 1 - July 15 (south) and April 15 - July 15 (north) IF new stumps are treated. (4) Do not harvest or conduct activities that may wound oaks April 1 - July 15 (south) and April 15 - July 15 (north). (8)	No restrictions July 16 - September 30. (12) 15	No restrictions October 1 - March 31 (south) and April 14 (north). (12)
In county & in stand	First consider owner interest in oak wilt control; otherwise, no restrictions April 1 - July 15 (south) and April 15 - July 15 (north) if new stumps are treated. (4) First consider owner interest in oak wilt control; otherwise, do not harvest or conduct activities that may wound oaks April 1 - July 15 (south) and April 15 - July 15 (north). (8)	First consider owner interest in oak wilt control; otherwise, no restrictions July 16 - September 30. (12)	First consider owner interest in oak wilt control; otherwise, no restrictions October 1 - March 31 (south) and April 14 (north). (12)

[a] South denotes stands located south of the tension zone in Wisconsin; north denotes stands located north of the tension zone. Wisconsin's tension zone is a border between northern and southern floristic provinces (Curtis 1959). Data on average monthly temperatures and flight of oak wilt insect vectors support use of different risk dates for these portions of the State.
[b] Twelve scenarios are possible for each timing-proximity combination. Number of scenarios to which the particular guideline applies is stated in parentheses.

topographic relief, oak wilt is most common on upper slopes and ridge tops (Anderson and Anderson 1963, Bowen and Merrill 1982, Cones and True 1967).

Each of the 108 stand condition scenarios described by combinations of the five factors was assessed for overall risk of oak wilt occurrence based on the individual criterion ratings. Overall risk ratings were high to very high for eight stand-condition scenarios where oak wilt was not known to be present in the stand (Table 3). Overall risk rating of very low, however, was often determined by a late fall–winter timing for the harvest.



To obtain oak wilt risk rating and associated guidelines, answer the following questions:	Codes	Enter your responses in the grey boxes
1) Is oak wilt present? Choose one of the responses below:		
Oak wilt not present in the county.	NN	
Oak wilt present in the county, but not known to be in the stand.	YN	
Oak wilt present in the county and the stand	YY	
2) What time of the year do you propose cutting? Choose one of the responses below:		
April 1 to July 15 - south of tension zone.	SPS	
April 15 to July 15 - north of tension zone.	SPS	
July 16 to Sept. 30 statewide.	SEF	
Oct. 1 to March 31 if south of tension zone.	FWN	
Oct. 1 to April 14 if north of tension zone.	FWN	
Note: If uncertain about tension zone location, please see Figure 2 (to right).		
3) What is the basal area (BA) of red oak in the stand? Choose one of the responses below:		
15 ft²/acre or less	L	
15 to 35 ft²/acre	M	
greater than 35 ft²/acre	H	
4) What is the general topography of the stand? Choose one of the responses below:		
Flat to rolling land or 0 - 12% slope.	FR	
Hilly with valleys or > 12% slope.	HV	
5) What is the general soil texture of the stand? Choose one of the responses below:		
Light textured (e.g.,sandy, loamy sand, sandy loam, sandy clay loam, and loam) or	L	
Heavy textured (sandy clay,clay, clay loam, silt, silt loam, silty clay loam, and clay loam)	H	
Note: The light and heavy textured soils were described by using the soil triangle, please see Figure 3 (to right).		

Figure 1—Query section of user page of spreadsheet application for oak wilt risk rating and associated management guidelines. Shaded boxes are where user enters information.

Timber Harvest Guidelines

Preventive measures developed for minimizing initiation of new oak wilt infection centers and the potential for future tree losses owing to oak wilt in regenerated stands were described in three brief statements: (1) Do not harvest or conduct activities that may wound oaks, (2) Harvesting may be conducted if stumps are treated, and (3) No restrictions. The first two measures largely apply to stand harvest activities being considered for spring and early summer. A summary of the stand/harvesting scenarios associated with each of the preventive recommendations when categorized by timing and proximity factors is presented in Table 4. For timber stands where oak wilt centers already exist and harvest of and regeneration to oak are planned, the guidelines include some further considerations. Specifically, foresters are advised to first consider the landowner's tolerance for future tree losses to oak wilt in the regenerated stands. Disease control actions, such as stump extraction or soil trenching, could be valuable for greatly reducing the carryover of oak wilt into the future stand.

Risk Analysis and Guidelines Tool Formats

Three different formats of the risk analysis results and the harvest guidelines were developed for end users. A hard-copy, decision-tree format (filename: oakwiltguide031507.

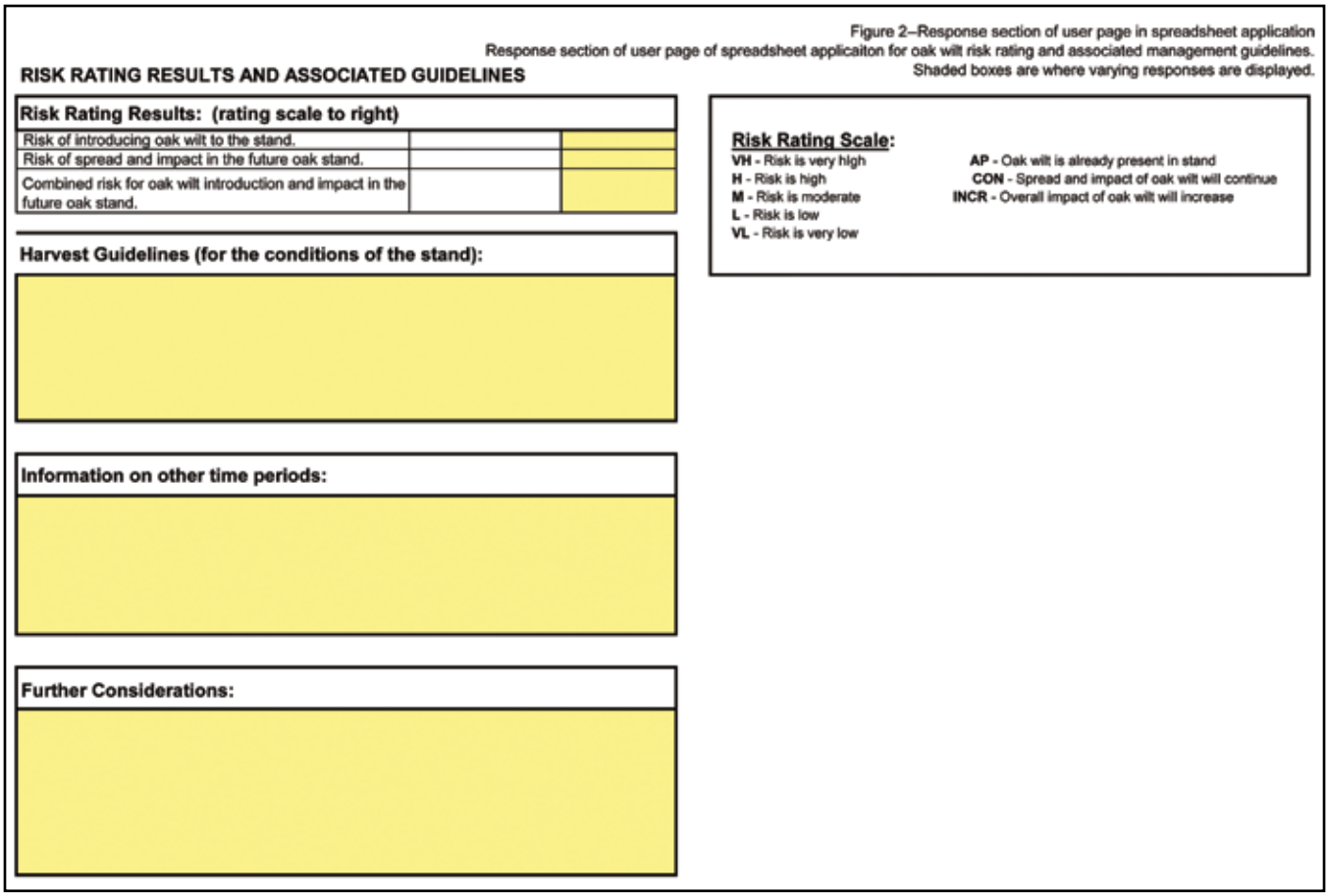


Figure 2—Response section of user page of spreadsheet application for oak wilt risk rating and associated management guidelines. Shaded boxes are where varying responses are displayed.

pdf) with accompanying tables is available from the Wisconsin DNR Web site (http://dnr.wi.gov/forestry/fh/oakWilt/guidelines.asp). The electronic spreadsheet version of the results (filename: oakwiltguide031507.xls) is also available from the same site. The interactive, online format was adapted from the spreadsheet version. The front user page of the spreadsheet-based tool (Figure 1) and of the online tool requires the user to input conditions of the stand being considered for harvest. The questions asked of the user include (1) Is oak wilt present? (2) What time of the year do you propose cutting? (3) What is the basal area of red oak in the stand? (4) What is the general topography of the stand? and (5) What is the general soil texture of the stand? The user selects a response from the multiple-choice answers offered for each question. The spreadsheet application then selects and displays the appropriate ratings and recommendations for the conditions described by the user (Figure 2), as does the online version.

Discussion

The rule-based, expert-driven model used in an exotic pest risk analysis context (North American Forestry Commission 2004) was adapted for use in assessing risk of oak wilt introduction to and potential for subsequent spread within oak timberland based on spatial, temporal, and site factors. Such a system may be useful for analyzing spread and impact risks in the management of other significant forest diseases. The Wisconsin DNR plans to use the same approach to analyze risk and develop guidelines for reducing spread of *Heterobasidion annosum* in pine forests of the State. The model was also considered for use in modifying existing guidelines for managing oak wilt in urban and

periurban forests of Wisconsin. Existing guidelines were, however, considered sufficiently robust and did not warrant such an effort.

The success of our approach relied on a collaborative planning and decisionmaking environment. The participatory method sought and obtained the involvement of multiple experts, stakeholders, and end users. The committee responsible for developing the criteria, conducting the risk analysis, formulating guidelines appropriate to risk ratings, and reviewing the prerelease product met for 4 hours on each of 4 days. Solicitation of stakeholder and user response and suggestions to the proposed system occurred over a 7-month time period through presentations and subsequent comment sessions held at numerous meetings, e.g., the Wisconsin Chapter of the Society of American Foresters' annual meeting and the Wisconsin Woodland Owners' Association annual meeting.

Several research questions were raised during the exercise of developing criteria, conducting the risk analyses, and developing guidelines appropriate for the assigned risks. The need for observed frequency or estimated probability for successful overland transmission of the oak wilt fungus between mid-July and early October is being addressed in a 3-year study initiated in summer 2006. Questions were also raised about the ultimate quantitative impact of oak wilt introduced during shelter wood preparatory cuts or clearcutting on future oak stocking in stands regenerated on dry and dry-mesic sites. On the basis of results of a West Virginia study (Tyron and others 1983), we hypothesize that the impact would be low in areas where regeneration is mostly of seedling origin. However, where coppice or stump-sprout regeneration predominates, the ultimate impact of oak wilt on stand stocking would likely be higher. A long-term study is needed to address these questions. New knowledge or previously overlooked scientific knowledge pertinent to our risk assessment system will be considered in future revisions of the product.

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Modeling Current Climate Conditions for Forest Pest Risk Assessment

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Abstract

Current information on broad-scale climatic conditions is essential for assessing potential distribution of forest pests. At present, sophisticated spatial interpolation approaches such as the Parameter-elevation Regressions on Independent Slopes Model (PRISM) are used to create high-resolution climatic data sets. Unfortunately, these data sets are based on 30-year normals and rarely incorporate up-to-date data. Furthermore, because they are constructed on a monthly rather than a daily time step, they do not directly measure simultaneous occurrence of multiple climatic conditions (e.g., days in the past year with appropriate temperature and adequate precipitation). Yet, the actual number of days—especially consecutive days—where multiple conditions are met could be significant for pest dispersal or establishment. For the sudden oak death pathogen (*Phytophthora ramorum*), we used National Oceanic and Atmospheric Administration daily weather station data to create current, national-scale grids depicting co-occurrence of multiple climatic conditions.

For each station, we constructed two count-based variables: the total number of days and the greatest number of consecutive days in a year where the station met several conditions (temperature, rain/fog, relative humidity). We then employed gradient plus inverse distance squared (GIDS) interpolation to generate grids (4-km^2 resolution) of these variables for 5 years (2000-2004). The GIDS technique weights standard inverse distance squared interpolation using coefficients based on geographic location (x, y) and a spatial covariate such as elevation. Using these variables, we determined the GIDS coefficients for each output grid cell via Poisson regression on the 30 closest stations. We also performed model selection to ensure only significant variables contributed to the GIDS coefficients.

We compared the GIDS approach to cokriging and detrended kriging using cross-validation and found similar accuracies among all three interpolation methods. We also compared the output grids to maps assembled from the PRISM data depicting the probability all conditions were met in a given year. As expected, we found differences in areas highlighted as suitable for *P. ramorum* establishment by the two methods. We suggest that using current weather data and calculating the variable of interest directly will provide more practical information for mapping forest pest risk.

Keywords: Climate, forest pests, GIDS, *Phytophthora ramorum*, risk, spatial interpolation.

Introduction

Forest pest risk assessments detail the nature and severity of threats posed to particular forest species and ecosystems by insects, pathogens, or other organisms (Andersen and others 2004a). With respect to nonindigenous forest pests, risk can be categorized or quantified based on a combination of factors: the potential for the pest to become established, the potential for it to spread following introduction, the potential to cause economic damage, or the potential to cause environmental harm (NAFC 2004). A commonly desired product of such assessments is a map depicting the threat posed by introduction or establishment of a forest pest throughout a geographic area of interest (Andersen and others 2004a). These maps can facilitate early detection and response procedures, providing a template for the design of regulatory programs and detection surveys. If a pest has already been established in one part of the geographic area of interest, threat assessment maps are used to help set control priorities for other geographic areas that are at high risk of invasion (Andersen and others 2004b).

Importance and Availability of Climate Information

Forest pest risk maps are typically assembled by combining spatial data from three principal subject areas: host species

distribution, pathways of pest movement, and key environmental factors (Bartell and Nair 2004). Climatic attributes such as temperature and moisture strongly shape pest behavior, affecting survival, reproductive rate, and in many cases, the ability to spread at a continental scale. Thus, climatic data provide an important coarse filter for forest pest risk analyses. Regularly gridded climate maps covering the entire geographic area of interest are typically required for analytical purposes. Such maps may be constructed by spatial interpolation of weather station data. These data are readily available for much of the United States, dating back several decades, from the National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center (NCDC).

Spatial Interpolation of Climatic Variables—
A wide array of spatial interpolation algorithms (e.g., geostatistical, regression, spline, inverse distance weighting) have been used to construct broad spatial-scale climatic data sets from weather station data (Daly 2006, Mardikis and others 2005, Nalder and Wein 1998, Price and others 2000, Xia and others 2000). Most currently accepted methods acknowledge that terrain is a significant factor governing climate at all but the broadest scales, and they use elevation measurements to represent terrain and adjust climatic variable values accordingly (Daly 2006). One well- received interpolation approach is the Parameter-elevation Regressions on Independent Slopes Model (PRISM). Initially developed to generate precipitation maps for the Pacific Northwest (Daly and others 1994), the approach has since been applied to create maps of temperature, relative humidity, snowfall, growing-degree days, and many other variables (Daly and others 2000). In particular, the PRISM approach was applied to generate most of the maps in the recent version of the Climate Atlas of the United States (Plantico and others 2002), as well as similar products for Canada and China (Daly and others 2000). The PRISM approach is a knowledge-based system integrating a local climate-elevation regression with other algorithmic com-ponents: station weighting, topographic facets, coastal proximity, and a two-layer atmosphere (Daly and others 2002). When initially tested on precipitation in the Pacific Northwest, the PRISM approach outperformed other interpolation methods in comparative analyses (Daly and others 1994).

Limitations of Existing Interpolated Climatic Data Sets—
There are several limitations of PRISM-derived or similar data sets with respect to their use for forest pest risk maps. First, most national-scale climatic data sets are calculated as normals, meaning an average of the variable of interest across a window of time, typically a 30-year period. For example, most data sets in the recent version of the Climate Atlas of the United States are based on inputs from 1961 through1990 (Plantico and others 2002). Current weather data are not incorporated into the maps, so any pest risk map constructed from them will not include current events—and the accompanying variability—that may be relevant to an assessment of immediate risk.

Second, there are related issues of cost and data format. The Climate Atlas contains polygonal maps for a large number of potentially relevant climatic normals but does not include the regularly gridded data from which the maps are derived. These polygonal maps have limited attribute resolution, with the range of the original gridded data typically compressed into nine or fewer classes. Monthly gridded maps of a few variables—precipitation amount, mean minimum temperature, mean maximum temperature, and mean dewpoint—are available for public download from the PRISM group at Oregon State University (http://www.ocs.orst.edu/prism/. [Date accessed unknown]). Notably, these maps are fairly current (finalized maps are available from 1997 through mid-2006), and the database is regularly updated, but it does not include many climatic variables that might be of interest for forest pest risk assessment (e.g., relative humidity, number of days above freezing, or number of days with measurable precipitation). Regularly gridded data of these and other (30-year normal) variables, derived using the PRISM method, are available, but at substantial cost (from the Climate Source: http://www.climatesource.com/. [Date accessed unknown]).

Third, most available climatic spatial data sets, whether derived using PRISM or other methods, are monthly or annual summaries depicting mean or extreme values over the time period. For some forest pests, the short-term,

even daily status of multiple weather conditions may be relevant to the pest's growth, persistence, or invasiveness. Fungal pathogens are particularly affected by the interaction of temperature and moisture availability. For example, the pathogen that causes late blight of potato (*Phytophthora infestans*) develops best at cool temperatures during extended periods of wet weather, as do many other *Phytophthora* species (Davidson and others 2002, Harvell and others 2002, Marshall-Farrar and others 1998). The interaction of climatic variables can also be important for some insect pests (Harrington and others 2001, Peacock and others 2006). Nevertheless, although there has been some effort to create maps of daily precipitation and temperature at a broad scale (Hunter and Meentemeyer 2005), there has been little attention paid to the co-occurrence of multiple weather conditions favorable to pest persistence and spread. Daily weather data allow the counting of how often, and for how long, variables meet certain threshold values. Creation of broad-scale maps from data derived in this manner may require a different spatial interpolation approach than that used for continuously distributed variables (van de Kassteele and others 2005).

Objectives

Given the limitations of existing climatic data sets, we explored the use of NCDC daily weather station data for the United States as an alternate source for maps relevant to forest pest risk assessments. We had three basic objectives: (1) spatially interpolate annual counts of the number of days with co-occurrence of multiple climatic variables relevant to the growth and spread of a specific forest pest—the pathogen that causes sudden oak death (*P. ramorum*); (2) identify a spatial interpolation method appropriate for count-based data and compare it to some common geostatistical approaches; and (3) assess the utility of the derived maps for depicting risk.

Case Study Species: *Phytophthora ramorum*

Phytophthora ramorum was first recognized in the United States in 1994 and was likely introduced via international trade of commercial plants (Ivors and others 2006). Since its introduction, the pathogen has infected western live and red oaks in coastal forests of California and Oregon, sometimes causing mortality greater than 40 percent (Garbelotto and others 2001, 2003). In addition, *P. ramorum* infects dozens of commercial shrub host species that can yield large numbers of aerially dispersed spores (Davidson and Shaw 2003, Davidson and others 2002, Tooley and others 2004). Many of these shrubs (e.g., rhododendrons, azaleas, camellias) are sold as nursery stock (Garbelotto and others 2001, Tooley and others 2004). In the past few years, wholesale nurseries on the west coast have unknowingly shipped infected plants to retail and wholesale outlets in roughly 40 States (Stokstad 2004), although surveys have not detected the pathogen in natural forests outside California and Oregon.

A large portion of the Eastern United States is considered at high risk for establishment of *P. ramorum* if it is introduced into forested areas. Much of the concern has to do with climatic conditions believed to be favorable for the pathogen. Growth, sporulation, and infection are all affected by moisture and temperature. Optimal temperatures for *P. ramorum* growth, based on laboratory analysis, appear to be between 64.4 °F and 71.6 °F (Werres and others 2001), but some growth occurs across a wider temperature range (up to at least 80 °F). Peak sporangia formation appears to occur at 59 to 68 °F (Davidson and others 2005). Persistent moisture on foliage is considered critical to spread. Laboratory inoculation trials on California bay laurel (*Umbellularia californica* (Hook. & Arn.) Nutt.), a major source of *P. ramorum* spores in California, suggest 9 to 12 hours of free moisture on leaf surfaces under appropriate temperatures are necessary for significant leaf infection (Garbelotto and others 2003). Further studies suggest that at least 24 to 48 hours of generally wet conditions are necessary for sporulation, with infection requiring additional time (Davidson and Shaw 2003, Davidson and others 2002, Rizzo and Garbelotto 2003). Fog and high relative humidity may be important for spread of aerial *Phytophthora* species within forest stands (Werres 2003), as high air moisture can keep leaf surfaces wet and enable spore production. Nevertheless, despite regular summer fog in California, *P. ramorum* sporulation and infection seem to be restricted to the winter-spring rainy season (Rizzo and others 2005).

Table 1—Number of NCDC weather stations used in interpolations

Year	Number of stations
2000	4,310
2001	4,258
2002	4,302
2003	4,144
2004	3,926

NCDC = National Climatic Data Center.

Isolated rains during otherwise dry summer months do not appear to facilitate spore production or dispersal (Davidson and others 2002). Ultimately, it is unknown how the pathogen's behavior on the west coast will translate to the Eastern United States, where warm season and cool season precipitation are similar (Akin 1991).

Methods

We downloaded 5 years (2000 to 2004) of daily surface data from the NCDC online climate data clearinghouse (http://cdo.ncdc.noaa.gov/CDO/dataproduct. [Date accessed unknown]). The downloaded data included dozens of climate variables recorded for more than 19,000 stations nationwide. We processed the data to extract four variables: total precipitation, minimum and maximum temperature, and relative humidity. For each station, we tallied (1) the total number of days and (2) the longest number of consecutive days in a given year that met the following conditions: maximum temperature greater than 60 °F, minimum temperature less than 80 °F, and at least a trace amount of precipitation or relative humidity of greater than 85 percent. These threshold values were selected to reflect current knowledge about the climatic conditions favorable for *P. ramorum* survival and spread.

We recorded the latitude, longitude, and elevation values for each weather station from an associated data set. We dropped any stations that fell outside the conterminous United States and any stations with more than 30 days of missing data for any variable in a given year. This filtering process reduced the number of usable stations (Table 1), but still yielded consistent national coverage. For stations missing 1 to 30 days of data, we normalized the total-day and consecutive-day count values by dividing them by the proportion of days in the year for which data were available and then rounding to the closest integer.

Gradient Plus Inverse Distance Squared Interpolation

We interpolated gridded maps of the conterminous United States for both the total-day and consecutive-day variables using a gradient plus inverse distance squared (GIDS) approach. This statistical method was first proposed as a way to interpolate climatic data on a broad spatial scale as input for plant growth models (Nalder and Wein 1998). The GIDS technique combines multiple linear regression with inverse distance weighting interpolation, and like other recently developed interpolation techniques, incorporates elevation as a covariate. For a given unmeasured location k and climatic variable Z, an ordinary least squares regression is performed using the N closest neighboring locations to calculate coefficients (C_x, C_y, and C_e) representing x, y, and elevation gradients: $Z = a + C_x X + C_y Y + C_e E + \varepsilon$, where a is the intercept and ε is error. Then, the basic GIDS formula is

$$Z_k = \frac{\left[\sum_{i=1}^{N} \frac{Z_i + C_x(X_k - X_i + C_y(Y_k - Y_i) + C_e(E_k - E_i)}{d_i^2}\right]}{\sum_{i=1}^{N} \frac{1}{d_i^2}}$$

where Z_k = the predicted value at an unmeasured location k, Z_i = the measured value at location i, X = the x-coordinate for the specified location, Y = the y-coordinate, E_i = the elevation value, and d_i = the distance from measured location i to Z (Nalder and Wein 1998).

Nalder and Wein (1998) compared GIDS with several other methods for interpolating monthly normals of precipitation and temperature in the Canadian boreal forest region. The tested methods included inverse distance squared weighting, nearest neighbor interpolation, ordinary kriging, universal kriging, co-kriging, and detrended kriging. Based on cross-validation using a held-out subset of the data, the GIDS method resulted in the lowest mean absolute errors (MAE), which averaged 0.5 °C for temperature and 3.6 mm, or 11 percent, for monthly precipitation. Price and

others (2000) compared the GIDS method with thin-plate moving splines and noted that GIDS, as an inverse distance approach, may have greater occurrence of extreme errors. However, they also noted its transparency and ease of use.

Modification of GIDS for a Count-Based Variable— The ordinary least squares regression implemented in the GIDS approach is intended for continuous, normally distributed variables. Because each of our variables of interest was a count, with large values being rare, we instead performed Poisson regression (Neter and others 1996). For each location of interest, we fitted a Poisson regression model, based on the 30 closest neighboring weather stations, using a maximum likelihood approach. We acknowledged that all three gradient variables (x, y, and elevation) could prove insignificant for a given prediction location and its closest measured neighbors. As a result, we evaluated a sequence of the full and all possible reduced models for statistical significance:

$\log(Z) = a + C_x X + C_y Y + C_e E + \varepsilon,$
$\log(Z) = a + C_x X + C_e E + \varepsilon,$
$\log(Z) = a + C_y Y + C_e E + \varepsilon,$
$\log(Z) = a + C_x X + C_y Y + \varepsilon,$
$\log(Z) = a + C_x X + \varepsilon,$
$\log(Z) = a + C_y Y + \varepsilon,$
$\log(Z) = a + C_e E + \varepsilon.$

For each prediction location, we tested all seven regression models using the 30 closest stations and identified those models in which all variables were significant. In cases where more than one of the models had all significant variables, we identified the one that yielded the smallest value for Akaike's Information Criterion (AIC). If the best-performing model was not the full Poisson regression model, then the coefficient(s) for any insignificant variable(s) were set to zero in the GIDS equation. If none of the tested models proved to have significant variables, then the GIDS interpolation reverted to inverse distance squared weighting (i.e., all variable coefficients were set to zero).

Interpolation Using GIDS— We implemented the Poisson-based GIDS formulation in a script written for R statistical software (R Core Development Team 2006), which we then used to interpolate values for cells covering the conterminous United States. We created a regular grid (with x, y, and elevation values) for the country by resampling an 8100-m^2 resolution digital elevation model (DEM) generated from U.S. Geological Survey data to 4-km^2 cells using a nearest neighbor method. Notably, this is the same spatial resolution used in most of the data sets that are publicly downloadable from the PRISM Group as well as the data sets available for purchase from the Climate Source (see "Limitations of Existing Interpolated Climatic Data Sets"). For each 4-km^2 cell, we determined the 30 closest NCDC weather stations using three-dimensional Euclidean distance measured from the cell's centroid. We rounded the GIDS-predicted value for each grid cell to the nearest integer.

Evaluation

For comparison to the GIDS-derived total-day and consecutive-day count maps, we created gridded maps for 2000 to 2004 using two spatial interpolation methods available through the ArcGIS Geostatistical Analyst extension (Johnston and others 2003). First, we performed cokriging on the count data using elevation as a covariate. Second, we performed detrended kriging, where we removed a second-order trend from the data and then performed ordinary kriging on the residuals. For both methods, we fit a spherical semivariogram model to the input data, calculating the model parameters (nugget, range, and sill) using a weighted least squares approach (Cressie 1993). As with the GIDS maps, we generated a predicted value for each 4-km^2 cell based on the 30 closest NCDC stations, and rounded the predicted value to the nearest integer.

We compared the accuracy of the three methods via station-by-station cross-validation. Using each interpolation method, we derived a predicted total-day and consecutive-day value for each station based on its 30 closest neighbors. We calculated errors by subtracting the actual observed counts for each station from the interpolated values. We then calculated three mean error measures: mean error (ME) indicates bias (positive = over-prediction, negative = underprediction); mean absolute error (MAE) indicates the magnitude of error regardless of sign; and root mean square error (RMSE) is sensitive to outliers and can be used to

Table 2—Interpolation method comparison for total-day variable[a]

	Interpolation Method	2000	2001	2002	2003	2004
Mean	Observed	62.94	61.77	58.77	64.43	70.32
	GIDS[b]	63.44	62.21	59.23	64.93	70.86
	Cokriging	62.97	61.81	58.89	64.64	70.36
	Detrended kriging	62.98	61.79	58.79	64.41	70.37
RMSE	GIDS	13.52	13.13	12.82	13.42	14.27
	Cokriging	13.07	13.07	13.19	14.35	14.00
	Detrended kriging	13.22	12.85	12.52	13.39	14.09
MAE	GIDS	10.39	9.97	9.61	10.14	10.81
	Cokriging	10.10	10.03	9.94	10.92	10.59
	Detrended kriging	10.24	9.82	9.44	10.18	10.66
ME	GIDS	0.508	0.438	0.464	0.500	0.532
	Cokriging	0.033	0.037	0.114	0.216	0.029
	Detrended kriging	0.046	0.018	0.025	-0.018	0.040

[a] Cross-validation results for each interpolation method based on five annual data sets. Errors calculated as observed values minus the predicted values; see text for interpretation of root mean square error (RMSE), mean absolute error (MAE), and mean error (ME).
[b] GID = gradient plus inverse distance squared.

assess the magnitude of extreme errors (Daly 2006, Nalder and Wein 1998).

To provide a basic visual reference, we used 30-year normal PRISM-derived data sets to construct U.S. maps depicting the total number of days and longest string of consecutive days when weather conditions are typically favorable for *P. ramorum*. We started with 12 monthly grids depicting the number of wet days (i.e., the number of days with precipitation) throughout the conterminous United States. For each monthly wet-days grid, we masked out any cells where temperatures did not fall within the 60 to 80 °F range at some time during the month. Using map algebra, we added the 12 monthly grids together to develop a total-day count for each grid cell in our output map. The consecutive-day count map was, by necessity, more approximately constructed. First, we standardized values in each of the masked monthly grids by converting the number of wet days to a proportion (number of wet days / total number of days in the month) and then multiplying this proportion by 30. Then, using map algebra, we recorded the maximum standardized monthly value for each cell in our output map. This approximated the range of values in the GIDS-derived consecutive-day maps. Nonetheless, because we used monthly rather than daily data to build the PRISM-derived maps, any comparison to the GIDS-derived maps must be done with care.

Results

In terms of cross-validation errors, the three spatial interpolation methods performed similarly for both the total-day and consecutive-day count variables (Tables 2 and 3). The GIDS approach, as suggested by the ME values as well as the actual versus the predicted means, tended to over-predict slightly more than the other two techniques. The RMSE results indicate that, for some years, the GIDS approach yielded a few more extreme errors, although GIDS had a lower RMSE than cokriging for the total-day variable in 2002 and 2003, as well as a lower MAE in 2001, 2002, and 2003. In general, error differences among the three were not substantial, with MAE consistently holding at approximately 16 percent of the total-day mean value and 25 percent of the consecutive-day mean value for all three techniques.

The GIDS-derived maps for the two count variables (Figures 1 and 2) most obviously show a great deal of annual variability. For the consecutive-day variable, the

Table 3—Interpolation method comparison for consecutive-day variable[a]

	Interpolation method	2000	2001	2002	2003	2004
Mean	Observed	5.73	5.72	5.21	6.03	6.25
	GIDS	5.78	5.77	5.25	6.08	6.30
	Cokriging	5.74	5.73	5.21	6.04	6.25
	Detrended kriging	5.73	5.74	5.20	6.03	6.25
RMSE	GIDS[b]	2.14	1.98	1.89	2.15	2.35
	Cokriging	2.10	1.97	1.83	2.14	2.30
	Detrended kriging	2.09	1.98	1.85	2.15	2.30
MAE	GIDS	1.46	1.41	1.28	1.51	1.62
	Cokriging	1.44	1.41	1.24	1.51	1.59
	Detrended kriging	1.45	1.42	1.25	1.51	1.60
ME	GIDS	0.053	0.052	0.039	0.048	0.051
	Cokriging	0.009	0.009	-0.001	0.006	-0.002
	Detrended kriging	0.005	0.018	-0.007	0.003	-0.001

[a] Cross-validation results for each interpolation method based on five annual data sets. Errors calculated as observed values minus the predicted values; see text for interpretation of root mean square error (RMSE), mean absolute error (MAE), and mean error (ME).
[b] GID = gradient plus inverse distance squared.

Eastern United States generally tended to have higher values than the Western United States, with parts of the Appalachian Mountain region and States along the Gulf of Mexico typically exhibiting high values. However, the extent and spatial distribution of the highest-value area fluctuated substantially year to year. The total-day maps exhibited a similar spatial pattern, but more clearly highlighting some relatively high-value areas in the southern and central Rocky Mountains. Perhaps unsurprisingly, the patterns of the GIDS-derived maps were quite different than the patterns depicted in the PRISM-derived maps.

Discussion

Four main points of emphasis emerge from the results. First, for the tested data sets, the interpolation method did not significantly influence the resulting error. There are several possible explanations for this. Foremost, although the GIDS approach may be technically more appropriate than geostatistical approaches for count-based variables, the Poisson model may not have been a good fit for these data, or the data may have been approximately normal enough to remove any advantage of a Poisson-based process over geostatistical approaches. Furthermore, among weighted-average interpolation approaches—a category that includes GIDS—kriging is often the best unbiased predictor for data that are not normally distributed (Johnston and others 2003). Another count-oriented approach—Poisson kriging—has recently emerged in health geography and ecological literature, and this may be a promising future direction for count-based spatial interpolation (Goovaerts 2005, Monestiez and others 2006). In the meantime, GIDS has a number of positive characteristics. It violates fewer assumptions than geostatistical approaches—in particular, the assumption of second-order stationarity (Cressie 1993). Furthermore, the GIDS approach is transparent and easily implemented. To use more complex approaches, particularly PRISM, requires estimation of numerous parameters, so a certain degree of subjectivity is involved. The GIDS approach can easily accommodate covariates besides elevation, and, in fact, could easily be adapted for multiple covariates in order to refine the results. Finally, the GIDS approach has been implemented in R code (R Core Development Team 2006), and as such is an open source resource that may be more readily available than GIS-based interpolation approaches.

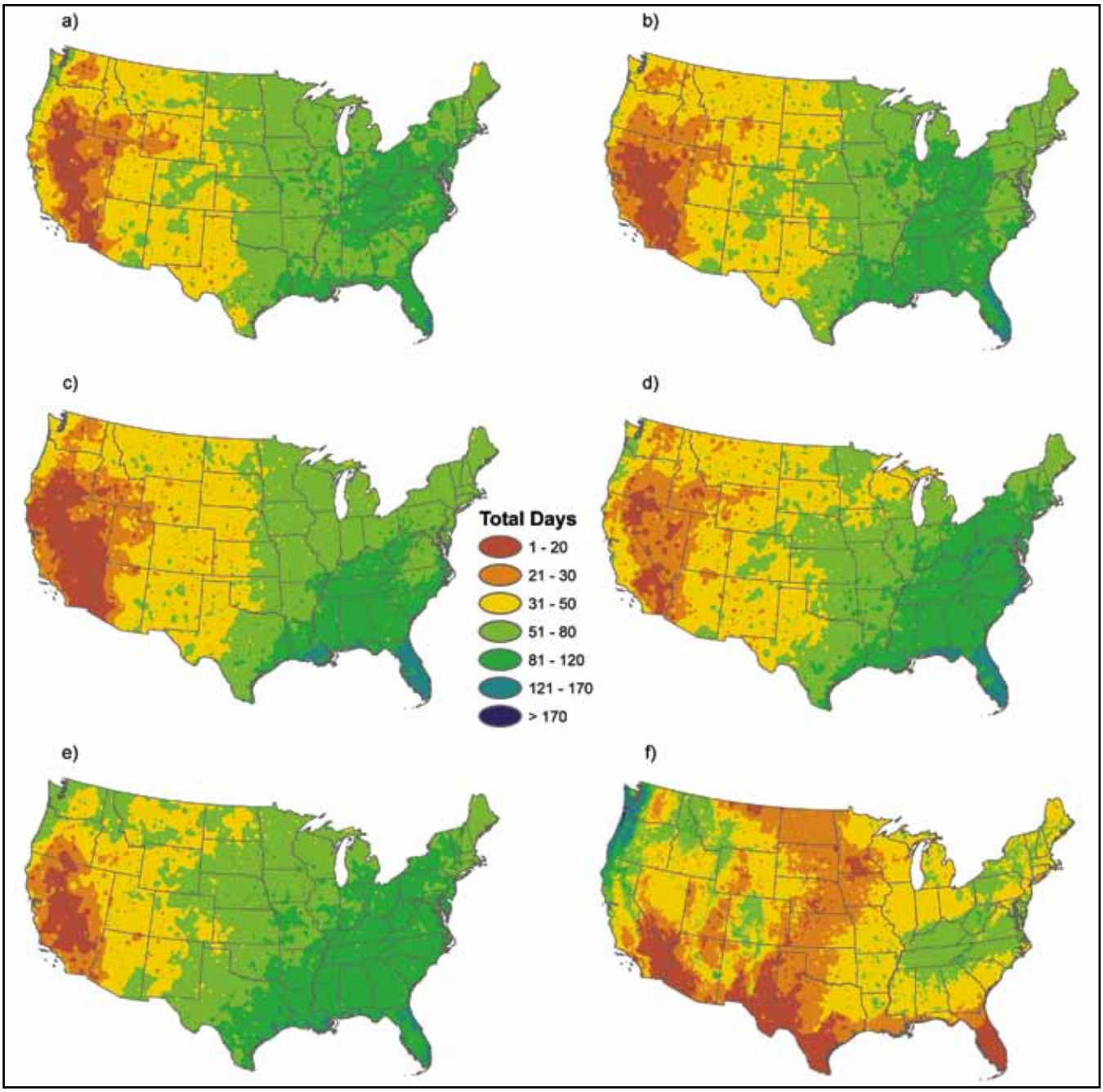

Figure 1—Annual maps of the total number of days with weather conditions favorable for *Phytophthora ramorum*, interpolated using the gradient plus inverse distance squared method: (a) 2000, (b) 2001, (c) 2002, (d) 2003, and (e) 2004; (f) for visual comparison, a total-day map approximated using monthly Parometer-elevation Regressions Independent Slopes Model.

Second, the interpolations of the two-count variables appear to have an acceptable degree of error. The distribution of cross-validation errors for the GIDS interpolations are revealing in this regard. For the consecutive-day variable, across all 5 years, only 25 percent of values were exactly predicted, but nearly two-thirds of predicted values were within 1 day of the observed value. For the total-day variable, only 4 percent of values were exactly predicted, but nearly 50 percent were within 5 days and greater than 75 percent were within 10 days. This should be adequate for

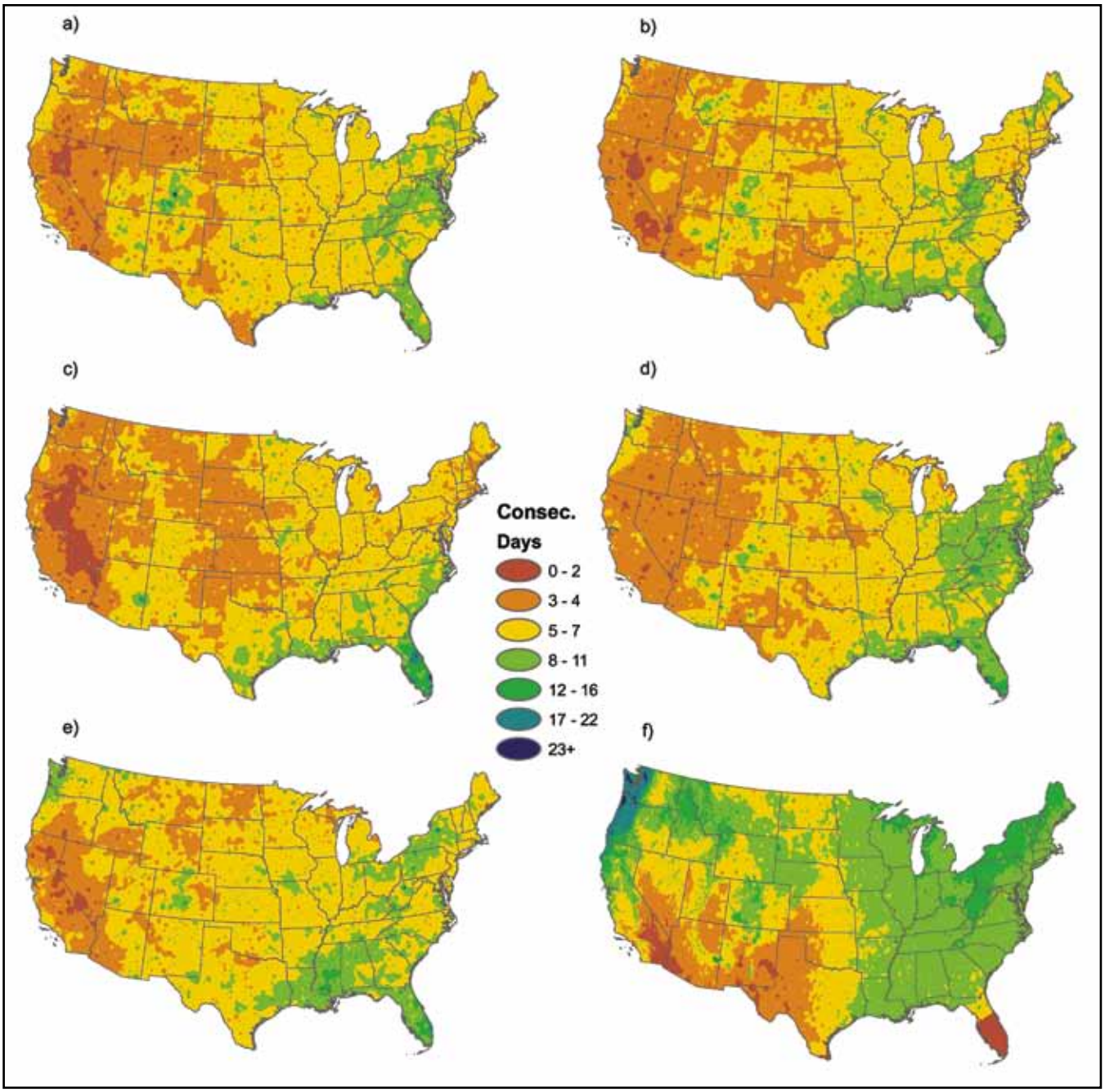

Figure 2—Annual maps of the longest string of consecutive days with weather conditions favorable for *Phytophthora ramorum*, interpolated using the graident plus inverse distance squared method: (a) 2000, (b) 2001, (c) 2002, (d) 2003, and (e) 2004; (f) for visual comparison, a total-day map approximated using monthly Parometer-elevation Rrgressions Independent Slopes Model

broad-scale ranking of areas according to their relative risk based on climatic and weather conditions.

The third and perhaps more important point is that the information provided by the constructed annual count maps is substantially different from results that can be captured using monthly climatic data sets based on 30-year normals. For *P. ramorum* and other currently emerging threats, it may be advantageous to identify areas that have exhibited favorable conditions in a given year and determine whether, for example, the pathogen was positively detected at any

nurseries in those areas during that time period. In fact, this suggests a need for a regularly updated database, and the GIDS method may be one way to generate a regularly updated data set from the NCDC data. Recent annual maps can be used in conjunction with 30-year normal data to create a strong picture of current risk.

Fourth, if the count-based variables we calculated are reasonable representations of the level of favorable climatic conditions for *P. ramorum*, then this suggests that large portions of the Eastern United States—perhaps more than originally estimated—have periods during each year where they may be especially susceptible to infection. Because climate and weather may not be severely limiting factors, detailed analyses of potential pathways and potential host species distribution may be in order for much of the Eastern United States.

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