MANAGING FOREST ECOSYSTEMS

Computer Applications in Sustainable Forest Management

Including Perspectives on Collaboration and Integration

Edited by
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Chapter 10

DIGITAL FORESTRY IN THE WILDLAND-URBAN INTERFACE*

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Abstract: Growing human populations have led to the expansion of the Wildland-Urban Interface (WUI) across the southeastern United States. The juxtaposition of buildings, infrastructure, and forests in the WUI creates challenges for natural resource managers. The presence of flammable vegetation, high rates of human-caused ignitions and high building densities combine to increase risks of catastrophic loss from wildfire in the WUI. At the same time, fragmentation of large ownerships into smaller parcels and changing demographics may limit the possibilities for managing fuels with prescribed fire. To make effective decisions in this environment, land managers will need to integrate a large volume of information characterizing the physical features, biological characteristics, and human dimensions of these landscapes. Remote sensing and Geographic Information Systems (GIS) technologies are crucial in this regard, but they must also be integrated with field surveys, fire behavior models, and decision-support tools to carry out risk assessments and develop management plans for the WUI. This chapter outlines the types of geospatial datasets that are currently available to map fuels and fire risk, provides examples of how GIS has been applied in the WUI, and suggests future directions for the integration of GIS datasets and spatial models to support forest management in the WUI.

Key words: Wildland-Urban Interface (WUI); Geographic Information Systems (GIS); spatial modeling; wildfire risk; fuel reduction; prescribed fire.

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1. INTRODUCTION

Changing human demographics have altered landscape patterns and created new challenges for forest management in the southeastern United States. Sprawling development at the peripheries of urban areas and increasing population densities in rural areas have expanded the Wildland-Urban Interface (WUI), where homes and other buildings are adjacent to, or intermixed with, flammable vegetation. These new land-use patterns have created challenges for natural-resource managers, whose job is to sustain timber production, wildlife habitat, and water quality in forested areas while protecting homes, infrastructure, and natural resources from fire. Historically, prescribed understory burning was widely used to reduce fuel loads and fire risk, while maintaining critical ecological processes in the South's fire-adapted ecosystems. However, concerns over safety and liability related to smoke and escaped fires can limit the applicability of prescribed fire in the WUI. Alternative strategies for mitigating wildfire damage include mechanical or chemical fuel-reduction treatments, as well as educational programs aimed at helping homeowners develop fire-resistant landscapes.

A simple map of WUI boundaries would provide useful guidance for managers, who must designate appropriate fuel-reduction treatments for different locations, and prioritize these treatments to reduce fire risk. However, heterogeneous patterns of both forest cover and human settlement across the South belie this characterization of the WUI as a static and discrete management unit. Instead, it is more realistic to conceptualize the WUI as a dynamic set of social, physical, and biotic gradients. Computer technology is a valuable asset to managers, who must integrate large volumes of information to make decisions in this spatially and temporally variable environment (Figure 10-1). Global positioning system (GPS) technology and remotely sensed imagery can be used to map vegetation and fuels as well as physical and anthropogenic features. Geographic information systems (GIS) provide the framework for storing, manipulating, and analyzing this spatial information. Computer simulation models of fire behavior and vegetation dynamics can be applied to project changes through time and evaluate the consequences of alternative management scenarios.

In this chapter, we focus on the problem of fuel management in the southeastern United States as a case study for exploring the digital forestry paradigm (Zhao et al. 2005). At the national level, a major goal of the National Fire Plan is to facilitate the application of fuel-reduction treatments for mitigating the hazard of uncharacteristic wildfire. The application of geospatial technologies to map vegetation and fuels, predict fire behavior and effects, and model the effectiveness of various strategies for fuel management has emerged as a cornerstone of these efforts. We recognize that the challenge of managing the WUI encompasses more than just fuel management. Other important concerns include the impacts of land-use change on wildlife habitat, the introduction of exotic species, and the influences of ownership changes and parcelization on timber supply (Macie and Hermansen 2002). Our goal here is not to provide a comprehensive review of management issues related to the WUI, but instead to highlight examples of how multiple digital information technologies can be integrated to support fuel management and fire-hazard reduction. The strengths and weaknesses of existing approaches are discussed, and suggestions for expanded implementation of digital forestry are provided.

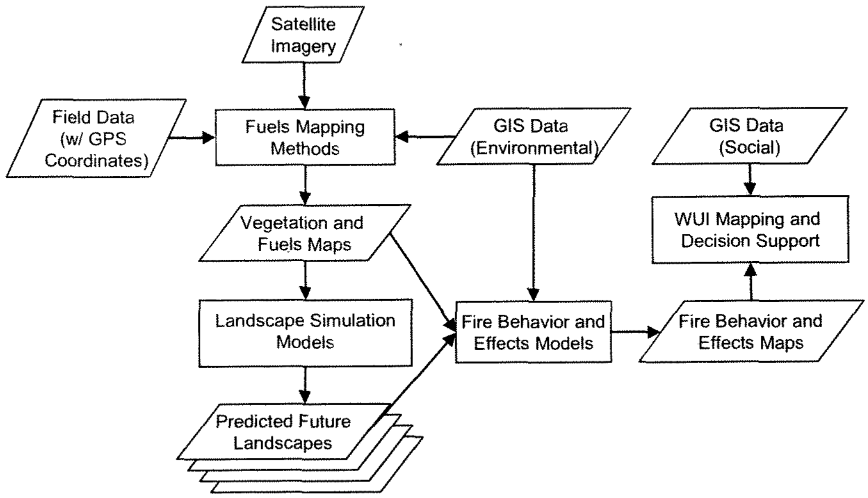

Figure 10-1. Flowchart illustrating the integration of multiple digital datasets and models for fire risk assessment and fire management in the Wildland Urban Interface.

2. DEFINING THE PROBLEM

In the United States, the popular conception of forest fires often focuses on large conflagrations in the western states. However, wildfire is also a common occurrence in the Southeast, where vegetation growth and fuel accumulation are rapid and ignitions from both lightning and humans are frequent. Fires in the Southeast have the potential to develop into large, dangerous conflagrations, as epitomized by the Volusia fire (111,130 acres) and the Flagler/St. John fire (94,656 acres), both of which occurred in Florida in 1998. Even though the annual wildfire acreage is relatively small compared to the western United States, the high density of homes and other structures across most of the Southeast result in a high potential for wildfire-related losses (Monroe 2002). High population densities increase the possibility of smoke-related health problems, even in areas that are far removed from the actual flames (Fowler 2003). The spatial juxtaposition of buildings and vegetation can create a conundrum for firefighters; homes must be protected, but the diversion of resources to defend structures can allow a fire to grow and threaten larger areas. Given these myriad challenges, it is not surprising that the present-day policies are focused on fires in the "intermix," or WUI (Pyne et al. 1996).

Fuel reduction is currently a major focus of fire management in the WUI. Unlike weather and terrain, the two other components of the fire behavior triangle, fuels can be modified through prescribed burning or mechanical treatments. Prescribed burning is often the preferred method for fuel management, because it is inexpensive compared to alternative mechanical treatments, and is particularly effective at reducing the fine surface fuels that have the greatest influence on fire behavior. However, the use of prescribed burning in the WUI can be constrained by negative public perceptions, potential risk of escaped fire, and air-quality and smoke-management regulations and health issues (Haines et al. 2001). Mechanical and chemical alternatives to prescribed burning are available, but these are usually more expensive, and may actually cause short-term increases in levels of fine fuels and the potential for extreme fire behavior (Brose and Wade 2002).

The potential for applying prescribed fire as a fuel-reduction treatment also depends on disturbance history and current stand conditions. In the absence of fire, autogenic succession in most southern pine forests leads to late-successional communities dominated by hardwoods. Fuel loads increase as succession progresses, but also shift from pyrogenic grasses and pine litter to less-flammable hardwood fuels (Maliakal et al. 2000). Increased overstory cover provides shelter from solar radiation and wind, leading to higher levels of understory fuel moisture (Streng and Harcombe 1982). Thus, it can be difficult to reintroduce fire into long-unburned stands under weather conditions considered acceptable for prescribed burning (Menges and Hawkes 1998). Fire-excluded stands can still carry fire, when fuel moisture is low enough, but burning under these conditions can result in extreme fire behavior and high levels of overstory tree mortality (Plocher 1999). In these cases, some type of mechanical fuel treatment will be needed before fire can be reintroduced.

Fire management in the Southeast, however, encompasses much more than just fire prevention and fuel reduction. Prior to European settlement, fire regimes, dominated by frequent, low-severity surface fires, created relatively open forests, ranging from pine savannahs of the Coastal Plain to hardwood-dominated forests in the Piedmont and the Southern Appalachians (Cowell 1995, Black et al. 2002). Fires resulted from a mixture of lightning and human ignitions, with mean fire return intervals ranging from less than 5 years in coastal plain pine forests plain to several decades in the Piedmont and the Southern Appalachians (Wade et al. 2000). The important role of fire in these ecosystems is evidenced by the large number of fire-adapted trees, including longleaf pine (*Pinus palustris*), and many native oaks (*Quercus* spp.). Frequent surface fires also foster diverse understory plant communities (Kirkman et al. 2001) and provide open habitat for endangered species such as the red-cockaded woodpecker (*Picoides borealis*) (James et et al. 2001). Thus, the overarching challenge for fuels and fire management in the Southeast is to sustain the role of fire as an ecosystem process, while at the same time minimizing the risk of uncontrolled wildfire, and the negative impacts of smoke.

3. APPLICATIONS OF DIGITAL FORESTRY CONCEPTS

3.1 Mapping vegetation and fuels

Information about the quantity and quality of fuels is necessary for predicting fire behavior, and evaluating potential fire effects. When assessments are expanded to large landscapes, the spatial configuration of the fuel mosaic must also be considered. Spatial patterns of fuels, topography, and wind all interact to influence fire spread and intensity. Fuels are of particular interest from a management perspective, because they can be modified through mechanical treatments or prescribed burning. Fuel maps can provide valuable information about the total amount of land in need of fuel-reduction treatments, as well as the locations of major areas of fuel accumulation.

Aerial photography and satellite remote sensing have proved to be effective technologies for mapping forest vegetation at landscape to regional scales. However, the mapping of forest fuels presents greater challenges than general land-cover classifications. For predicting potential surface-fire behavior, the most important fuels include leaf litter, dead branches, and the foliage of live shrubs, grasses, and herbaceous plants. These surface fuels have traditionally been classified into a small number of stylized fuel models (Anderson 1982), although new and expanded classification systems have recently been developed (Sandberg et al. 2001, Scott and Burgan 2005). Surface fuels are often hidden beneath the forest canopy, and may be too fine grained to discern from remote imagery, even if the understory is visible. Because of these problems, surface fuels are usually mapped indirectly, based on assumed relationships with one or more overstory attributes that can be inferred from image texture or spectral signatures. For example, fuel loadings may vary with stand age and overstory basal area (Wade et al. 2000), or differ among major forest-cover types (Hely et al. 2000). When using this approach, the application of GPS technology is critical for linking field-based assessments of understory fuels with imagery and GIS databases.

Remotely sensed imagery, acquired from aircraft and satellites, has been used to map surface fuels in a variety of landscapes. Oswald et al. (2000) mapped surface-fuel models in East Texas by interpreting aerial photographs, and predicting fuel models based on percent pine composition, pine basal area, and crown closure. Similarly, Welch et al. (2002) developed a fuel map for the Great Smokey Mountains National Park by linking surface-fuel models to 25 generalized overstory vegetation classes that were interpreted from aerial photographs. Brandis and Jacobsen (2003) mapped surface-fuel loads in New South Wales, Australia, based on characteristics of the forest canopy obtained from Landsat TM imagery. They applied models of litterfall and decomposition to translate estimates of canopy biomass into steady-state fine fuel loadings. Van Wagtendonk and Root (2003) mapped vegetation classes and associated surface-fuel models in Yosemite National Park using seasonal trends in Normalized Difference Vegetation Index (NDVI) measured with Landsat TM.

An alternative to traditional aerial photo interpretation or image classification is the predictive vegetation-mapping approach (Franklin 1995). Statistical models are used to predict vegetation characteristics using a combination of remotely sensed imagery and GIS layers describing climate, topography, and other biophysical variables. The incorporation of additional information, in the form of GIS datasets, is generally believed to improve mapping accuracy beyond that obtained with remote-sensing imagery alone. Rollins et al. (2004) mapped surface-fuel models in the Kootenai River Basin of northwestern Montana using Landsat TM bands, a digital elevation model (DEM), and climate maps. Reich et al. (2004) mapped surface-fuel loadings in the Black Hills of South Dakota using Landsat TM bands, a DEM, and a forest-cover type map. Falkowski et al. (2005) mapped surface-fuel models in northwest Idaho, based on structural stages, cover types, and potential vegetation types derived from ASTER imagery and topographic variables.

For predicting the risk of crown fires, maps of canopy variables, such as canopy bulk density and height to the base of the live canopy, are needed (Scott and Reinhardt 2001). Canopy closure and stand height are also necessary to model reductions in wind speed caused by the forest canopy. Compared to surface fuels, these canopy variables have a more direct influence on the spectral response of the forest overstory. Canopy bulk density is correlated with leaf-area index (LAI), and has been mapped using Landsat TM imagery (Perry et al. 2004), and ASTER imagery (Falkowski et al. 2005). However, spectral vegetation indices are insensitive to LAI variability in dense, closed-canopy stands (Asner et al. 2003), and are likely to exhibit a similar response to canopy bulk density. Estimates of tree height and height to base of the live canopy must be indirectly derived from spectral variability related to overstory canopy structure (Lefsky and Cohen 2003). Active remote sensing technologies such as sensors for light detection and ranging (LIDAR) hold particular promise for improved mapping of three-dimensional canopy structure. LIDAR has been used to measure canopy attributes such as volume, mass, bulk density, and height to base in loblolly pine forests in Texas (Roberts et al. 2005), pine forests in central Spain (Riano et al. 2004), and Douglas-fir forests in the Pacific Northwest, USA (Andersen et al. 2005).

A major challenge in fuel mapping is the need for consistent estimation of multiple variables, while maintaining a realistic correlation structure. For example, a spatial model of fire effects might require maps of fuel models, stand height, and canopy closure to predict behavior of surface fire, along with maps of tree species and sizes to predict vegetation responses. Keane et al. (2000) dealt with this problem by using a classification approach. They first defined strata by overlaying potential vegetation classes derived from terrain modeling with cover types and structural stages derived from Landsat TM imagery. A look-up table was then used to assign representative canopy variables and surface-fuel models to each stratum. Wimberly et al. (2003) used the Gradient Nearest Neighbor (GNN) method (Ohmann and Gregory 2002) to simultaneously predict multiple vegetation attributes and fuel variables in Coastal Oregon based on Landsat imagery and environmental variables. This approach combined a multivariate predictive model (Canonical Correspondence Analysis) with imputation of forest inventory data to assign representative plots to all locations in the landscape.

3.2 Delineating the wildland-urban interface

The intermingling of humans and natural systems in the WUI affects a variety of resource values, including water quality, wildlife habitat, and timber production. A topic of particular concern is the heightened risk of high-severity wildfire in the WUI. In this context, risk encompasses both the probability of an unwanted occurrence (wildfire), and the potential consequences of its occurrence (ecological degradation or loss of property and lives). Although fuel maps can be used to identify areas of high fuel accumulation, sufficient resources are usually not available to apply fuel-reduction treatments to all of these areas. Additional information on the locations of objects at risk, such as people and buildings, is needed to identify where fuel-reduction treatments will lead to the greatest reduction in fire risk. If arson or accidental ignitions are major sources of wildfire, humans can also impose a feedback loop that increases wildfire probability in the WUI (Cardille et al. 2001).

The U.S. Census is the major source of spatial information on human demographics in the United States (Peters and MacDonald 2004). Similar datasets are available for many other countries. The spatial units of the census are mapped at 1:100,000 scale, and are organized in a nested spatial hierarchy, comprised of blocks, block groups, tracts, and counties in order of increasing size. These units are scaled to a target population size. For example, census blocks typically have a population of 85 people, and are therefore much larger in rural areas than in urban areas. At the block level, only limited information about population and household densities is released. At the block-group level and above, additional information on education, income, time of residence, and a variety of other demographic variables are available.

Census data are particularly useful for measuring low-density development in forested areas that can be difficult to detect using satellite imagery (Theobald 2001). However, the large sizes of census blocks in rural areas limits the spatial precision with which patterns of housing units can be mapped (Figure 10-2a). Furthermore, many types of buildings, such as schools, hospitals, and industrial facilities, are not included in the count of housing units. Although these types of buildings are likely to be correlated with housing density at very broad scales, they can not be identified from the census data at small scales. Thus, additional sources of spatial data on human populations will be necessary, when the goal is to develop more detailed, local assessments.

Another type of spatial information reflecting human demographics and land use is the pattern of roads. At regional scales, road densities are correlated with housing densities, and the intensity of human land use (Hawbaker et al. 2005). In rural areas, individual buildings are more likely to be located close to a road than far from one (Figure 10-2b). Furthermore, the roads themselves can have a strong effect on landscape structure, wildlife habitat, and probability of wildfire ignition (Forman 2002). The TIGER/Line files produced by the U.S. Census contain data on roads and other transportation networks for the entire United States at 1:100,000 scale. Road datasets at larger cartographic scales (1:24,000 or greater) provide higher spatial accuracy, and are often available through state or local agencies. Other potentially valuable spatial data for wildfire assessments in the WUI include maps of individual buildings, parcels (Figure 10-2c), utility lines, hospitals, schools, airports, or other features that could be affected fire or smoke. Typically, these types of GIS datasets are maintained by county and local governments, and are not readily available at a regional level. One relatively straightforward approach to mapping the WUI is to overlay land cover and census data using a rule-based approach. This method has been used to classify urban, interface, intermix, and wildland areas across the entire United States (Radeloff et al. 2005). Interface areas were identified using Boolean logic, based on a minimum housing density, a maximum vegetation cover, and a threshold distance to one or more large forested blocks. Intermix areas were classified based on minimum housing and vegetation densities. The results of this study emphasize the ubiquity of the WUI in the southeastern United States. Large percentages of the total land area in Alabama (24%), Georgia (26%), Tennessee (30%), South Carolina (34%), North Carolina (44%), and Virginia (34%) are classified as WUI. Percentages of housing units occurring in the WUI are even higher, ranging from 53% to 71% in the states listed above. However, there is considerable variability in ignition probabilities, fuel characteristics, and structure densities within these areas, and not all the lands classified as WUI are at high risk from wildfire. More detailed subregional analyses are needed to identify areas within the WUI where there is a significant threat of wildfire occurrence and resulting economic losses.

Maps of the WUI can be refined, if additional data on fuels, topography, and cultural features are available. The state of Florida used this approach in their Florida Fire Risk Assessment System (FRAS) (http://flame.fl-dof.com /risk/). A susceptibility index for wildland fire was mapped by predicting potential fire behavior, based on fuels, vegetation, topography, and historical weather, and overlaying these predictions with a map of historical fire locations. An index of fire effects was mapped by integrating spatial information on human populations, natural resources, and critical infrastructure elements with estimates of costs for fire suppression. These two indices were combined into a final map of fire risk. Zhang (2004) developed a generalized WUI index that combined GIS layers describing forest cover, household density, road density, slope, aspect, forest community type, and ownership. Landscape-level relationships were incorporated by using a 1-mile-radius moving window to summarize forest cover, housing, and roads. These methods were used to develop localized WUI maps for the southern Appalachian highlands along the northwestern boundary of Great Smoky Mountains National Park, and for the South Atlantic Coastal Plain in the vicinity of Tallahassee, FL (Zhang 2004).

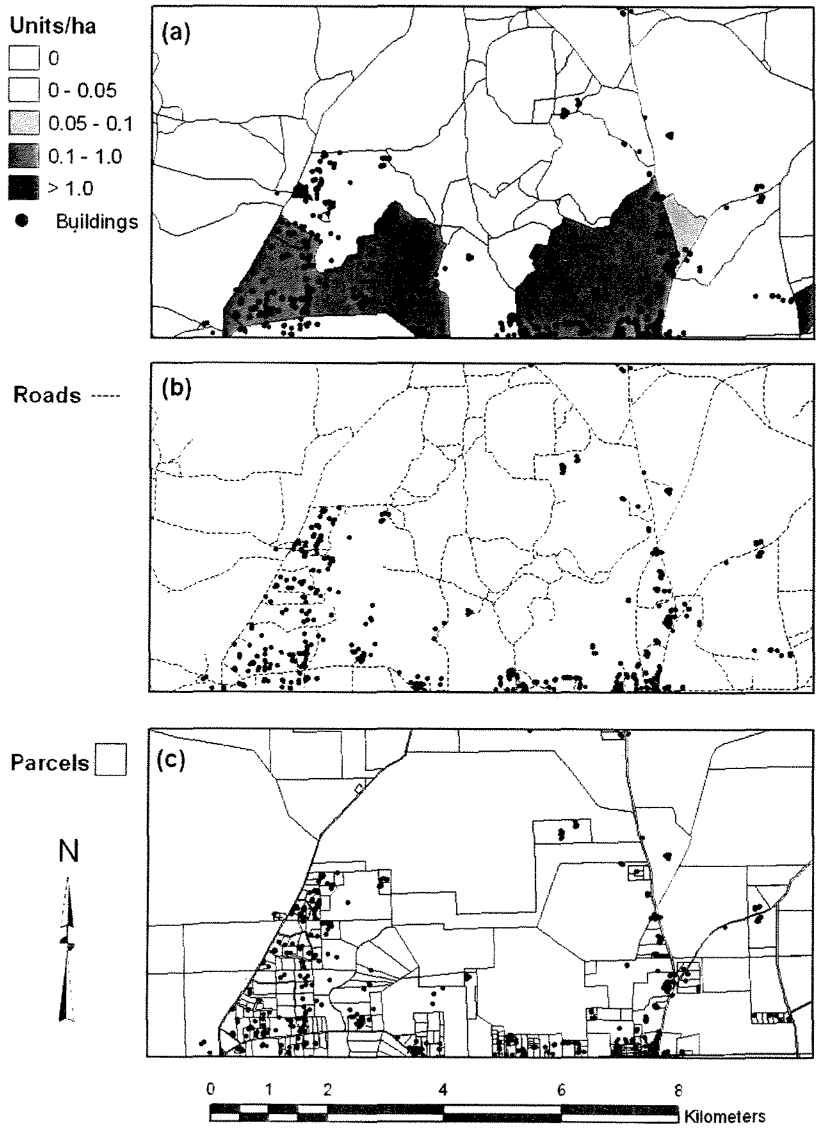

Figure 10-2. GIS datasets characterizing human habitation and infrastructure in northeastern Leon County, FL. a) Housing-unit density from the 2000 census at the block level; b) County-maintained roads; c) Parcel boundaries. Dots represent mapped building locations from 2003.

4. FUTURE DIRECTIONS

4.1 Uncertainty analysis

All maps derived from remote sensing have inherent error, usually expressed as a confusion matrix, in which ground-truth data are compared with predicted map classifications. Statistics derived from this confusion matrix include the percentage of observations correctly classified, along with errors of omission and commission. When continuous variables are mapped, predicted map values can be plotted against measured ground values, and the strength of the relationship assessed by the coefficient of determination. Reported accuracy levels for maps of surface fuels vary, ranging from 54.3% correctly classified for a map of 7 fuel models in Yosemite National Park (Van Wagtendonk and Root 2003) to 69.2% for a map of 3 fuel models in Kootenai River Basin (Rollins et al. 2004). In making this type of cross-study comparison, it should be noted that classification accuracy is expected to increase as the number of mapped classes decreases (Cohen et al. 1995).

The implications of this uncertainty for the use of maps in assessments of fire risk are not clear. Even if vegetation and fuels maps have considerable errors at the pixel or patch level, they may still be useful for generating aggregate predictions across larger land units. However, relatively small variations in map accuracy may translate into large changes in the spatial patterns represented in the map (Shao et al. 2001). Traditional error assessments of remote-sensing data products do not explicitly consider the spatial distribution of errors, although new methods for detailing spatial error are emerging (Plourde and Congalton 2003).

A particularly promising methodology uses geostatistics and stochastic simulation to generate a distribution of equally probable maps, given the observed level of map error. Viewing these multiple realizations of a map provides a way for users to visualize the amount and spatial pattern of uncertainty. A large sample of alternative maps can be generated and run through subsequent models and analyses in a Monte Carlo approach to quantify the impacts of error propagation on the conclusions drawn from a GIS analysis (Kyriakidis et al. 1999, Kyriakidis and Dungan 2001). It would be illuminating to carry out such an analysis with fuel maps and fire behavior models to assess the degree to which map error influences subsequent predictions of fire behavior and effects.

4.2 Enhanced mapping of the wildland-urban interface

Efforts at mapping the WUI to date have focused on combining spatial information on vegetation, fuels, and fire hazard with the geographic distribution of structures that are potentially at risk from fire. However, the WUI has much broader impacts on both ecological and social values than just fire risk. Some of these other factors may ultimately feed back and influence the potential for carrying out fuel-reduction treatments in the WUI. For example, objectives for habitat management for some species may conflict with the need to alter forest structure to reduce fire risk. GIS-based models for wildlife habitat (e.g., Liu et al. 1995, Cox and Engstrom 2001) have been developed for a wide range of species, and could be integrated with assessments of fire risk to gain a broader picture of potential impacts on natural resources resulting from wildland fire, or from treatments designed to reduce the risk of fire.

The same social forces that have created the WUI also limit the applicability of some management practices for reducing fire risk. For example, thinning of merchantable trees can lower canopy bulk density and reduce the risk of active crown fires (Agee and Skinner 2005). In the southern pine flatwood forests, commercial thinning also temporarily reduces the loadings of live and dead surface fuels (Brose and Wade 2002). However, as human populations increase, and forested ownerships are divided into smaller parcels, the potential for commercial timber harvesting decreases because of declining economies of scale, increased value of land for uses other than forestry, and changing landowner values and objectives. Analyses of forest inventory data from a number of southern states support this contention. Rates of timber harvest decline with decreasing tract sizes in Virginia (Thompson and Johnson 1996), South Carolina (Thompson 1997), and Florida (Thompson 1999).

Increasing population densities in the WUI also present challenges for use of prescribed fire as a management tool because of negative public perceptions, and potential liability resulting from smoke and escaped fire (Miller and Wade 2003). Air-quality regulations may result in restrictions on the use of prescribed fire in and around locations designated as federal non-attainment areas for particulate matter (Riebau and Fox 2001). These concerns make implementing prescribed burning and other types of fuel treatments more costly in the WUI than in more rural areas (Berry and Hesseln 2004), and will reduce and ultimately eliminate the use of prescribed fire in many areas as human populations increase. In the south-central United States, the frequency of prescribed burning decreased with increasing population density, and was lower on nonindustrial private forestlands than on public lands (Zhai et al. 2003). In Florida, the use of prescribed burning was also negatively related to population density, and more prevalent on public than private lands (Butry et al. 2002).

These types of management constraints can be modeled and displayed in a GIS context. As an example, we created a map of the potential for commercial timber harvest based on a study by Wear et al. (1999). Their research found that as human population density increased from 20 to 70 people per square mile, the probability of commercial timber harvest (PCH) decreased from approximately 75% to 25%. In this context, variability in population density is assumed to be correlated with several proximal factors that influence forest management including parcel size, land values, and landowner objectives. Results from this study were extrapolated across central Virginia by predicting PCH as a logistic function of population density at the census-block level. The percentage of forested land cover in each census block was also computed using the NLCD land cover dataset from the early 1990s (Vogelmann et al. 2001). A WUI index was then generated for each census by multiplying (1 – PCH) by the percentage of forested landcover within each census block (Figure 10-3).

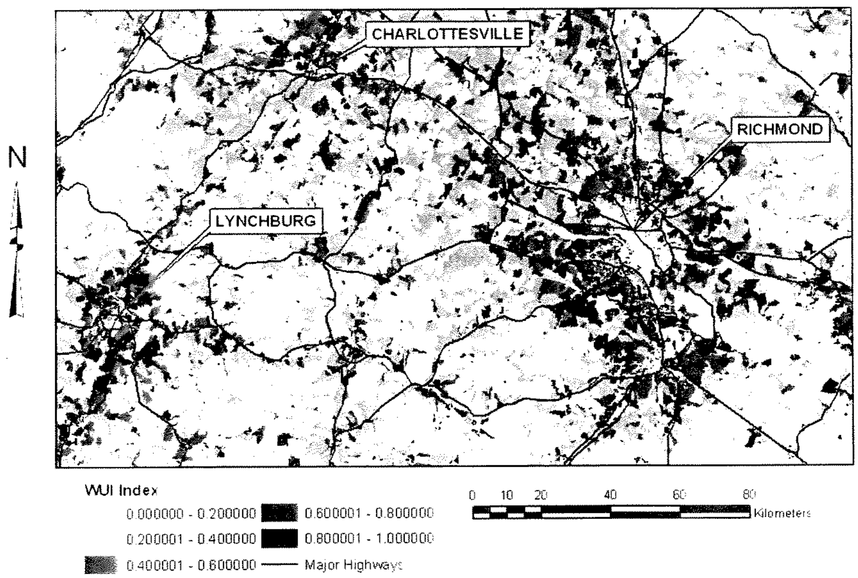

Figure 10-3. WUI index, reflecting potential constraints on commercial timber harvesting in central Virginia, and modeled as a function of forest cover and population density.

High values of the index identify areas where forest cover and fuels are abundant, but where fuel treatments linked to thinning or other silvicultural operations are unlikely to be commercially viable because of dense human populations. In contrast, low values of the index identify areas where forest cover is low (cities and agricultural areas), or forested rural areas where silvicultural activities are likely to occur. Not surprisingly, the highest index values are located on the outskirts of cities and along major transportation corridors – the same areas where structures are at greatest risk from wildfire and fuel-reduction treatments are most needed. This type of model can be refined, if additional spatial data on forest-tract size, transportation networks, and processing facilities are available. Similarly, maps of prescribed burning potential could be developed based on the spatial pattern of neighborhoods, roads, hospitals, and other smoke-sensitive areas.

4.3 Decision support

The ultimate step in applying the paradigm of digital forestry to the WUI is to link digital spatial databases with analytical tools for evaluating alternative strategies for fire management and fuel reduction. One approach is to use simulation models to study interactions between spread of fire and the spatial pattern of fuel treatments. Modeling studies in hypothetical landscapes can be used to derive general conclusions about treatment effectiveness. Experiments with a probabilistic cellular-automata-based model demonstrated that spread of fire could be greatly reduced by fuel treatments that comprised a relatively small proportion of the landscape, and that a regular pattern of fuel treatments was more effective than a random pattern (Loehle 2004). More sophisticated physically-based models of fire spread, such as FARSITE (Finney 1998), can account for spatial variability in fuels and terrain along with temporal variability in weather and fuel moisture. These types of models can also be applied in hypothetical landscapes to compare the effects of various treatment patterns on rates of spread and levels of fireline intensity (Finney 2001), or used to assess potential fire behavior in real landscapes, if geospatial datasets characterizing fuels, vegetation structure, and topography are available (Duncan and Schmalzer 2004, Stratton 2004).

Temporal as well as spatial patterns of fuel-reduction treatments must ultimately be considered in the development of effective strategies for fuels management. In the absence of fire, plant communities change through autogenic succession. These changes are typically accompanied by increased fuel loads as litter accumulates, and understory vegetation grows (Wade et al. 2000). Although prescribed fire can greatly reduce fine surface fuels and live understory biomass in southeastern forests (Brose and Wade 2002, Waldrop et al. 2004), fuel loads will recover rapidly without repeated burns. Natural disturbances, such as tornadoes, hurricanes, and insect outbreaks, can add to fuel loads and increase fire intensity (Liu et al. 1997). Mechanical treatments such as thinning reduce canopy bulk density, and decrease future litter and branch inputs, but can also temporarily increase fine fuel loads, if logging residue is left on site (Waldrop et al. 2004). Thus, fuel maps and models of fire behavior must ultimately be integrated with models of vegetation dynamics, fire effects, and other disturbance agents.

Several individual-tree-based models of forest dynamics have been extended to incorporate fuel loading and fire effects on forest vegetation (Keane et al. 1990, Miller and Urban 1999, Reinhardt and Crookston 2003). Changes in forest structure and composition are projected using equations that predict tree establishment, growth, and mortality, based on competitive interactions with other trees in a stand. Fire is incorporated by tracking fuel inputs from litterfall and tree mortality, fuel decomposition, fire intensity as a function of fuel loads, and fire-induced tree mortality as a function of fire intensity, tree species, and tree sizes. To scale up to the landscape level, patch-level models can be linked to polygon features within a GIS to reference spatially varying model inputs, and to allocate model projections to specific locations on the landscape (Keane et al. 1996, McCarter et al. 1998, Li et al. 2000).

An alternative approach to landscape modeling is to use a simpler, rule-based model to simulate vegetation transitions for individual cells within a raster GIS framework. An example of this type of model is LANDIS 3.7, which models forests as different-aged cohorts of species within each cell (He and Mladenoff 1999b). Flammability can be modeled as a simple function of time since the last fire and the local environment, or can be tracked more explicitly by modeling inputs to, and outputs from, broad fuel classes (He et al. 2004). These simplifications make simulations more efficient, and allow models like LANDIS to focus more explicitly on landscape-scale spatial processes such as seed dispersal, management activities, and fire spread (Gustafson and Crow 1999, He and Mladenoff 1999a, b).

Scientists and managers have only recently begun integrating these new geospatial datasets and models to address fire- and fuel-management problems at broad spatial and temporal scales. In most cases, they have applied a relatively straightforward simulation approach in which a small number of alternative scenarios are assessed through a modeling experiment. LANDIS has been applied to compare the effects of six forest management scenarios on risk of canopy fire (Gustafson et al. 2004), and to assess the influences of three fuel-reduction strategies on fuel loads and probability of burning in the Missouri Ozarks (Shang et al. 2004). A project to assess fire risk in the southern Oregon Cascades linked a geospatial database with stand-level forest-growth simulations, landscape-level fire initiation, and fire spread models to compare potential burned areas and other ecological criteria between two management scenarios (Roloff et al. 2005).

Although these types of simulation experiments allow comparison of treatments, their results are constrained by the small number of scenarios typically chosen for study. In most cases, there are other, more effective solutions to problems in forest planning. Modeling frameworks have been proposed for optimizing the placement of fuel treatments on a landscape to minimize the risk of large, destructive fires (Hof and Omi 2003). However, solving these problems, using traditional optimization techniques such as linear or integer programming, is not feasible when spatial relationships and processes must be incorporated at the landscape level. The development and application of models for landscape planning to derive optimal strategies for fuel treatment represents an important area of ongoing research in the arena of digital forestry. The SafeD model, for example, used a hybrid optimization and simulation approach that integrated computer-intensive heuristic optimization algorithms with GIS databases and models of fire spread and forest dynamics (Graetz 2000, Bettinger et al. 2004). Similar modeling approaches have been used to evaluate the effectiveness of fuelbreaks (Sessions et al. 1999), and are being developed to perform spatial optimization for location of fuel treatments (Finney 2004, Kim and Bettinger 2005).

5. CONCLUSIONS

The WUI presents a complex tableau in which the need for reducing fire risk must be balanced against a wide range of other social, economic, and ecological constraints. A major goal in managing the WUI is deciding how how to best allocate limited resources for fuel management and reduction of fire hazard. Effective planning will require the integration of large quantities of digital information from a variety of sources (e.g. fuel plots, remotely sensed imagery, DEM) with landscape simulation models and decision support tools. This information will also need to be shared by different administrative units working across multiple spatial scales. Although digital forestry offers promise for meeting these needs, there are still significant challenges that need to be addressed. The vegetation classes that can be readily mapped using remotely-sensed imagery will not necessarily meet the information needs of managers applying fuel treatments on the ground. Similarly, broad-scale, strategic assessments of the WUI that are valuable at a national level will not provide the amount of detail necessary to predict wildfire hazards and support management decisions at the local level. The geospatial datasets and simulation models used in these assessments contain varying levels of uncertainty, and the implications of these uncertainties for decision-support applications are not well understood. Future natural resource managers must be able to critically assess these data sources and model outputs to make effective decisions. Training in the conceptual and methodological aspects of digital forestry will therefore be critical in helping the next generation of natural-resource professionals to meet these challenges.

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