Evaluating Satellite Imagery–Based Land Use Data for Describing Forestland Development in Western Washington

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ABSTRACT

Forestry professionals are concerned about how forestlands are affected by residential and other development. To address those concerns, researchers must find appropriate data with which to describe and evaluate rates and patterns of forestland development and the impact of development on the management of remaining forestlands. We examine land use data gathered from Landsat imagery for western Washington and evaluate its usefulness for characterizing low-density development of forestland. We evaluate the accuracy of the satellite imagery–based land use classifications by comparing them with other data from US Forest Service's Forest Inventory and Analysis inventories and the US census. We then use the data to estimate an econometric model describing development as a function of socioeconomic and topographic factors and project future rates of development and forestland loss to 2020. We conclude by discussing how best to meet the land use data needs of researchers, forestry policymakers, and managers.

Keywords: land use change, forestland development, wildland-urban interface, Landsat

Forestry professionals increasingly are concerned about the ways in which forestlands are affected by residential and other development. Loss of forestland to development reduces the productive forestland base and our ability as a nation to produce timber and other forest commodities. It also reduces the many public benefits that forestlands provide to society, such as watershed and ecosystem protection, scenic vistas, and recreation. Studies suggest that development can be accompanied by changes in how neighboring private forest landowners manage their lands (Barlow et al., 1998, Wear et al., 1999, Munn et al., 2002, Kline et al., 2004, Vickery et al. 2009). These behavioral changes over time can influence forest characteristics, such as density, age class, species composition, and succession (Munn et al., 2002), with potential ecological and wildfire consequences. The loss of forestland to development has emerged as a significant contemporary federal policy interest, as exemplified by the US Forest Service's *Forests on the Edge* study (Stein et al. 2005) and the call for a national strategy to protect forestland as open space (US Forest Service 2006). Advancing policy and management objectives regarding forestland development and protection depends on identifying rates and patterns of development, evaluating their likely effects on private forest management, and anticipating future changes.

A significant challenge in meeting these objectives is finding appropriate data with which to describe and evaluate land use change and development at sufficiently fine spatial scales. State forestry and natural resource agencies often lack resources for gathering land use data on their own. Although nationwide land use data are available from sources such as the National Resources Inventory of the Natural Resources Conservation Service (e.g., Nusser and Goebel 1997) and the US Forest Service's Forest Inventory and Analysis (FIA) program (e.g., Frayer and Furnival 1999), these data are often too coarse for examining more localized management activities and ecological phenomenon. Forest managers and research ecologists, for example, often desire land use information at finer spatial resolutions (e.g., 30-m pixels) more relevant to the forest characteristics and ecological processes of interest. Some analysts have begun to use population and housing data from the US census (e.g., Radeloff et al. 2000, Theobald 2005), from which land use classifications can be developed, but because these efforts depend on data reported at US census block levels, the spatial resolution and potential accuracy of resulting maps tends to be coarsest in rural locations where forest use is most likely.

The National Land Cover Dataset, developed by the US Geological Survey (Vogelmann et al. 1998, Homer et al. 2004), offers greater spatial resolution and is widely used in national resource assessments and ecological research. However, the data set includes land cover classifications for just two points in time—1992 and 2001—and direct comparability between the two remains questionable because of the different methods and classification schemes used. Ideally, a greater number of temporal observations are desired. Moreover, image classification techniques on which these data are based have been criticized for their tendency to misclassify low-density development as forest cover. Some analysts even suggest that the data are systematically biased against recording low-density development (e.g., Irwin and Bockstael 2007, p. 20675). Part of the problem seems to arise from a focus on identifying land cover rather than land use. Land cover characterizes biophysical cover of the land surface; land use characterizes human uses of land such as for timber

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and commodity production, agriculture, and residential and other development. Although land cover sometimes can indicate land use (e.g., forest versus development), it is often not a good indicator of whether existing forestland is managed for timber and other forest commodity production. What would be useful is a cost-effective way to obtain data specifically designed to address the information needs of forest policymakers—data that can be used to characterize the extent of forestland development and its effects on private forest management.

We examine land use data gathered using multiresolution classification of Landsat imagery for western Washington, west of the crest of the Cascades (Rural Technology Initiative 2006). That data gathering effort, funded by the US Forest Service Pacific Northwest Research Station's FIA program, sought to test the feasibility of automating the interpretation of satellite imagery to produce data for describing and evaluating land use changes occurring on nonfederal lands, similar to data that FIA gathered over the past decade in collaboration with the Oregon Department of Forestry. Although highly useful, the Oregon data are based on fairly labor-intensive data gathering methods involving interpretation of aerial photos (Lettman 2002, 2004). The purpose of the western Washington effort was to see whether similar data of comparable accuracy could be developed faster and more cost effectively for other areas of the Pacific Northwest. In this study, we evaluate the accuracy of the western Washington land use classifications resulting from the automated process by comparing them to classifications reported by FIA inventories and population densities reported by the US census. We evaluate the usefulness of the data for policy analysis and management by estimating an econometric model describing development as a function of socioeconomic and topographic factors and compare development projections made using the model with those made by other studies using different data and methods. We conclude by discussing implications regarding how best to meet land use informational needs of forestry policymakers and managers.

Western Washington Land Use Data

The population of western Washington has increased rapidly over the last 25 years, resulting in expanded urban areas and fragmentation of forested and agricultural lands. The increase of forestland in the wildland-urban interface is believed to have implications for the economic viability of forest management focused on timber production, as well as the ecological sustainability of those same lands for habitat and the production of natural resource amenities and other ecosystem services. Increased demand for housing near urban centers, such as Seattle, Olympia, and Tacoma, has increased the value of forestland, often making development more financially appealing to landowners than managing for timber, wildlife, or other ecological values. Decreases in timber production, and in some cases the subsequent conversion of forestland to developed uses, could lead to economic and ecological concerns in the communities where such changes take place. For these reasons, forest policymakers and land use analysts have sought ways to better describe land use changes taking place in the region and their effects on forestry. Despite significant population growth and development in western Washington, much of the land use data and analysis available for the region had been characterized by fairly coarse (e.g., county-level) spatial scales (Alig and White 2007). Although useful for describing general trends, these data tend to constrain evaluation of likely management and ecological effects.

Land use data gathered in Oregon served as a model for data desired for western Washington. In a combined effort, the US Forest Service Pacific Northwest Research Station's FIA program and the Oregon Department of Forestry have developed and periodically updated spatially referenced data describing several discrete categories of land use, as well as building (or structure) counts, on nonfederal lands throughout the state (Lettman 2002, 2004). These data are gathered from high-resolution digital aerial photographs spanning the early 1970s to the present. By tracking land use on individual sample points from one sample period to the next, the data document changes among land use categories and increases in building counts over time. With 37,000 sample points statewide and three or four sample periods depending on region, the data set provides an outstanding resource for observing rates and patterns of land use change and evaluating its potential effect on private forest management in Oregon. However, data based on aerial photography can be time-consuming and costly to develop and update, especially if coverage is desired for relatively large states typical of the western United States. Procuring aerial photos themselves can be costly, difficult, and even sometimes impossible if historical coverage is desired. Aerial photo interpretation can also involve interpreter bias arising from differences in the way individual photo interpreters observe and record land uses. For these reasons, the FIA program sought to develop and test methods for gathering similar land use data from widely available satellite imagery at potentially lower cost.

As an alternative, land use data for western Washington used in this study were drawn from Landsat images for 1988, 1996, and 2004 using an automated interpretation process (Rural Technology Initiative 2006). The potential advantage of an automated process over photo interpretation is the cost savings that could be gained in future data gathering once an automated process is developed. Automation involved a two-step multiresolution classification process used to locate development within broad land cover classes (Rural Technology Initiative 2006, p. 4). Fine-scale images were used to identify "developed" image elements, such as buildings and roads, representing low-density or more intensive development. These classifications were combined with relatively coarser scale images used to locate general land cover classes of forest and agriculture. These two scales of information were used to segment pixels using the eCognition software application to identify relatively small built-up areas within larger forest tracts (Rural Technology Initiative 2006, p. 5). A set of decision criteria was then used to classify pixel combinations on the basis of combinations of land cover and development classes (Table 1). Land identified with forest or agricultural cover and largely absent significant development was classified as "wildland forest" or "agriculture." Land identified with forest or agricultural cover but with some development was classified as "other forest" or "mixed agriculture." Land identified as having more significant development was classified as "developed." The process resulted in GIS maps depicting land use for 1988, 1996, and 2004 (Rural Technology Initiative 2006, p. 21–23).

Similar to data needs in Oregon, the goal of land use data gathering in western Washington was to identify forestlands experiencing low-density or more intensive development to residential, commercial, industry, or infrastructure uses. The key questions addressed in this study include the following: (1) Are the data developed from automated processing of satellite imagery any better than data developed by more labor-intensive interpretation of aerial

Table 1. Land use classifications and descriptions used for remotely sensed data, compared to Forest Inventory and Analysis land use classifications and descriptions.

Land use	Description
Satellite imagery–based classifications[a]	
Wildland forest	At least 640 contiguous ac of forest cover of which no more than 5% is developed, and with no more than four structures per square mile.
Other forest	Land in forest cover that does not meet definitions for either wildland forest or developed.
Intensive agriculture	At least 640 contiguous ac of agricultural cover (crops and grassland) of which no more than 5% is developed, and with no more than nine structures per square mile.
Mixed agriculture	Land in agricultural cover that does not meet definitions for either intensive agriculture or developed.
Developed	At least 40 contiguous acres of which at least 20% comprise roads, homes, commercial buildings, and other development.
Forest Inventory and Analysis classifications[b]	
Forest	Land at least 10% stocked with live trees or that had such stocking in the past and is not currently developed for nonforest use.
Range	Natural grassland or pasture, nonforest marsh, or abandoned farmland.
Agriculture	Farmland, cropland, irrigated and/or artificially seeded grassland or pasture, and farmsteads.
Corridor	Constructed roads, power lines, pipelines, canals, and railroads.
Urban	Town sites and clustered suburbs, residential and industrial buildings, city streets, and developed parks.

[a] Based on classifications described in Rural Technology Initiative (2006, p. 17–18), but with rural forest included in wildland forest; other agriculture included with mixed agriculture; and low-density residential, high-density residential, and urban combined as developed.
[b] Based on Gray et al. (2005).

photos? and (2) Are the data useful for informing forest policymakers and managers about past and likely future trends in forestland development? To address the first question, we evaluated the accuracy of the satellite imagery–based land use classifications by comparing them with other data from FIA inventories and the US census of population. Ideally, use of both the aerial photo and satellite imagery–based methods over the same area would have enabled a direct comparison of data gathered using the two methods. However, funding limitations did not permit such parallel (or administratively redundant) data gathering efforts. We proceeded under the assumption that the aerial photo interpretation process used in Oregon resulted in data of fairly high accuracy and consistency because of the greater opportunity for subjective judgment by analysts relative to the automated approach used in Washington. A facet of the question thus involved assessing whether potential lower costs of an automated process outweigh any reductions in accuracy. To address the second question, we used the satellite imagery–based data to estimate an econometric model of land use change and project future forestland development through 2020.

Comparison with Land Use Data from Other Sources

We evaluated the land use classifications resulting from automated data processing of Landsat images by comparing them with other land use data gathered by the FIA program's periodic forest inventories (e.g., Gray et al. 2005) and population data reported by the census of population (US Census Bureau 2000). FIA data are particularly well suited for "ground-truthing" the remotely sensed land use data because general land use classifications for field plots are determined by field crew on the ground during plot visits. Comparison with census-reported population densities at FIA field plots enabled us to examine how well the land use classification processes distinguished between forested and developed lands.

General land use classifications used by the FIA program include forest, range, agriculture, corridor, and urban (Table 1). Although the precise definitions of these classes do not exactly match the criteria used to delineate land use classes from the satellite imagery, they do arguably provide a reasonable comparison. Since the 1960s, data gathered by the FIA program had been based on a systematic sample of field plots that were visited about every 10 years. Data gathered include detailed information about forest conditions and management activities, as well as general land use and ownership. The most recent complete inventory in western Washington was conducted in 1988–1990 (MacLean et al. 1992), providing a close match in time with the 1988 satellite data. The recent transition of the program toward a new, annualized inventory design that visits only a portion of field plots each year was initiated with a partial inventory conducted in 2000 to provide a baseline estimate of forest conditions and trends (Gray et al. 2005). These data are of limited usefulness for comparison because they do not match well with the 1996 or 2004 Landsat image dates and comprise a much smaller sample size. We focused our analysis on comparing the 1988 land use classifications with those from the 1988–1990 FIA inventory by sampling 1988 satellite imagery–based data using the FIA plot locations.

Cross-tabulation of land use classifications indicate that automated data processing of satellite imagery classified 93.0% of forested FIA plots as wildland forest and 2.9% as other forest, with smaller percentages classified as intensive agriculture, mixed agriculture, or urban (Table 2). Satellite imagery classifications of agricultural FIA plots were more varied, with 29% classified as wildland forest and smaller percentages classified as other forest or developed, suggesting potential misclassification of some FIA-identified agricultural lands. Most FIA plots identified as "corridor" were classified as wildland forest, other forest, or developed, which seems reasonable given the variety of land uses included in the FIA corridor definition. Satellite imagery classifications identified only 45.4% of urban FIA plots as developed, with the remainder classified as wildland forest, other forest, intensive agriculture, and mixed agriculture. Such misclassifications likely owe to the influence of tree cover and other vegetation present among what otherwise might be identified as urban uses by FIA inventory field crew. Some urban lands were not recognized as developed using the less subjective automated land use classification procedures applied to the satellite imagery. We feel that the cross-tabulations suggest cause for concern regarding the correct classification of agricultural and urban land uses. Moreover, although most forested FIA plots were "correctly" placed within wildland forest or other forest classes, the fact that forested FIA plots comprised 72.6% of the FIA plot sample indicates that a significant number of forested plots were misidentified using the satellite imagery land use classification procedures.

Table 2. Cross-tabulation (column %) of 1988 satellite imagery–based land use classifications with 1988–1990 Forest Inventory and Analysis[a] field plot classifications (n = 2,153).

Satellite imagery–based classification	Forest Inventory and Analysis classification					
	Forest[b]	Range	Agriculture	Corridor	Urban	Total
	(Column %)					
Wildland forest	93.0	59.1	29.0	73.5	27.9	77.8
Other forest	2.9	4.6	4.9	9.8	10.4	4.1
Intensive Agriculture	2.2	13.6	32.2	2.0	5.4	6.5
Mixed agriculture	1.5	18.2	25.8	3.9	10.9	5.8
Developed	0.4	4.5	8.1	10.8	45.4	5.8
Total (row %)	72.6	1.0	13.2	4.7	8.5	100.0

[a] Data from Gray et al. (2005).
[b] Includes 10 plots classified as Christmas trees.

Table 3. Upper quartile, median, and lower quartile population densities[a] by select cross-tabulated land use classifications from 1988 satellite imagery–based land use classifications with 1988–1990 Forest Inventory and Analysis (FIA) classifications on FIA field plots. Land use classifications are defined in Table 1. Select cross-tabulations are from Table 2.

Satellite imagery–based, 1988	FIA classification, 1990		
	Forest	Corridor	Urban
	(people/mi^2)		
Upper quartile			
Wildland forest	18	40	847
Other forest	38	94	3,256
Developed	3,306	4,599	5,263
Median			
Wildland forest	2	3	292
Other forest	2	23	1,306
Developed	1,182	288	2,382
Lower quartile			
Wildland forest	0	0	121
Other forest	0	16	395
Developed	102	0	797

[a] Based on 1990 block-level population densities reported by the US Census Bureau (2000).

Examination of population densities for different cross-tabulated land use classes provides additional evidence of potential satellite imagery–based misclassification of developed lands as wildland forest. We combined the FIA plots with block-level population densities reported by the US Census Bureau (2000). Although the measured areas of census blocks can be quite large relative to the point locations of FIA plots, leading to errors in reported densities at plot locations, especially in rural locations adjacent to urban areas, to our knowledge block-level data are the finest spatial resolution at which population density is reported. Median population density on urban FIA plots that were classified using satellite imagery as wildland forest was 292 people per square mile, and the upper quartile was almost three times as high, at 847 people per square mile (Table 3). Although the satellite imagery–based "other forest" classification was designed to include forestland with some development, those urban FIA plots classified using satellite imagery as other forest had a median population density of 1,306 people per square mile and an upper quartile of 5,263 people per square mile, suggesting that their FIA classification as urban likely was more appropriate in many cases.

On the other hand, forested FIA plots that were classified using satellite imagery as developed also had high population densities, with a median of 1,182 people per square mile and an upper quartile of 3,306 people per square mile (Table 3). Although this might suggest potential FIA misclassification of developed land as forest, FIA inventory procedures focus on identifying land use present at the exact location of FIA field plots. FIA criteria are intended to guide field crews to classify forestland as forest as long as the surrounding forest use comprises at least 1 ac of "forest" that is not being mowed, intensively grazed, or otherwise more intensively used. Thus, it is possible for field crew to identify land in a largely developed area as forest if it is tree-covered and does not show evidence of more intensive uses. Such comparisons reveal how procedures, classification criteria, and land use definitions greatly influence the data procured.

Modeling the Conversion of Land to Development

To examine the usefulness of the satellite imagery–based land use data for characterizing the process of forest development over time, we used the data to estimate an empirical model describing development as a function of explanatory variables hypothesized to influence land use change. A 3-km by 3-km grid of points was used to sample the three land use maps for 1988, 1996, and 2004 to create a set of observations of land use at each point in time. By tracking the land use classifications of sample points for successive years, we constructed a cross-sectional data set depicting where and when forest and agricultural land was developed between image years. After omitting observations comprising federal and state-owned land and already developed land, the sampling grid and procedure yielded 8,835 observations of development. We then defined a binary dependent variable describing whether or not forest or agricultural land was developed over either of the two 8-year periods of 1988–1996 and 1996–2004. A set of explanatory variables was constructed by sampling GIS maps depicting socioeconomic and topographic factors hypothesized to influence forest and agricultural land development. Selected explanatory variables included key socioeconomic and topographic factors shown to influence development in the Pacific Northwest (e.g., Kline and Alig 1999, Kline et al. 2001, Kline 2003, Kline et al. 2003, Kline et al. 2007) and are described in Table 4.

The influence of land's proximity to cities of varying sizes was characterized using a gravity index computed as

$$\text{GRAVITY INDEX}_i = \sum_{1}^{K} \text{POPULATION}_k \left(\frac{60 - \text{TIME}_{ik}}{60} \right),$$

where K is the number of cities within a 60-minute drive (or commute) of each observation i, POPULATION is the population (US Census Bureau 2000) of each city k, and TIME is the driving time in minutes between observation i and city k. The five cities included in the computation were Bellingham, Olympia, Seattle, Tacoma, and Vancouver, whose boundaries were located using a GIS map available from the Washington State Department of Transportation

Table 4. **Explanatory variables included in the logit model describing the likelihood that forest and agricultural land was converted to low-density or greater development, 1988–1996 and 1996–2006 (n = 8,835).**

Variable	Definition	Mean
Population density	People (in thousands) per square mile (US Census Bureau 2000) at initial year of change period, found by interpolating between census years.	0.071
ΔPopulation density	Absolute change in population density over duration of change period.	0.020
Gravity index	Equal to the average of the gravity index computed (using Equation 1) at the beginning of each time period and the gravity index computed at the end of each time period (times 1/100,000). City populations for observation years estimated by interpolating between populations reported for census years (US Census Bureau 2000).	0.127
Forest	Variable equals 1 if initial land use is wildland forest or other forest (Table 1); 0 otherwise.	0.877
Agriculture	Variable equals 1 if initial land use is intensive agriculture or mixed agriculture (Table 1); 0 otherwise.	0.123
Slope	Percentage change in elevation.	0.218
Elevation	Elevation (thousands of meters).	0.318
Time period	Variable equals 1 if change period is 1996–2004; 0 if change period is 1988–1996.	0.494
Spatial lag	Proportion of immediately neighboring sample points that converted from forest or agricultural land use to low-density or greater development during the change period (times 1/100).	0.017

Table 5. **Estimated coefficients of logit models describing the likelihood that forest and agricultural land was converted to low-density or greater development, 1988–1996 and 1996–2004. Explanatory variables are defined in Table 4.**

	Full model		Simplified model	
Variable	Estimated coefficient	Marginal effect	Estimated coefficient	Marginal effect
Constant	-5.007^a (-25.49)	-0.055	-4.624^a (-27.75)	-0.055
Population density	1.691^a (11.23)	0.019	1.742^a (11.70)	0.021
ΔPopulation density	1.213^a (7.12)	0.013	1.197^a (7.14)	0.014
Gravity index	0.724^a (7.26)	0.008	0.821^a (8.52)	0.010
Agriculture	1.371^a (7.90)	0.015	1.446^a (8.41)	0.017
Slope	-1.502^b (-2.21)	-0.017	-1.692^b (-2.48)	-0.020
Elevation	0.491 (1.30)	0.005	0.491 (1.30)	0.006
Time period	0.467^b (2.83)	0.005		
Spatial lag	3.605^a (4.99)	0.040		
Summary statistics	n = 8,835; log likelihood = -714.2; X^2 = 711.0; df = 8; $P < 0.0001$		n = 8,835; log likelihood = -730.7; X^2 = 730.7; df = 6; $P < 0.0001$	

[a] Probability that the t-statistic (in parentheses) for each coefficient exceeding the critical t-value is greater than 99%.
[b] Probability that the t-statistic (in parentheses) for each coefficient exceeding the critical t-value is greater than 95%.

(2004). Driving times to each city centroid were estimated using a GIS map of existing roads (Washington State Department of Transportation 2007). We assumed average speeds of 60 mph on interstate highways, 45 mph on state highways, and 10 mph on all other roads. As computed, the gravity index is the sum of populations of cities within a 60-minute commute of each observation, weighted by the estimated driving time to each city (Kline 2003, Kline et al. 2003).

Using these data, we estimated a logit model describing the likelihood that forest and agricultural observations were converted to developed uses from one imagery occasion to the next as a function of the explanatory variables. The actual model estimated was

$$\begin{aligned} \text{Logit}(\textit{Developed}) = \alpha_0 &+ \alpha_1(\text{POPULATION DENSITY}) \\ &+ \alpha_2(\Delta\text{POPULATION DENSITY}) \\ &+ \alpha_3(\text{GRAVITY INDEX}) \\ &+ \alpha_4(\text{AGRICULTURE}) \\ &+ \alpha_5(\text{SLOPE}) \\ &+ \alpha_6(\text{ELEVATION}) \\ &+ \alpha_7(\text{TIME PERIOD}) \\ &+ \alpha_8(\text{SPATIAL LAG}) + \varepsilon, \end{aligned}$$

where α_0 is a constant, the α_i are coefficients to be estimated, and ε is an error term. The spatial lag variable was included to test for the presence of spatial autocorrelation, which is common in land use data. Spatial autocorrelation can result from omitted spatial variables that influence the land-use decisions of landowners, such as weather, and spatial behavioral relationships, such as common ownership of sampled land parcels. The first leads to inefficient but asymptotically unbiased estimated coefficients, whereas the second can lead to inefficient and biased estimated coefficients (Nelson and Hellerstein 1997). Also, because the data generally include two observations of potential development for each sample point, there is the potential for correlation among observations across time to deflate standard errors and bias the estimated coefficients. To address this issue, we also estimated an alternative version of the model using logit with random effects (Greene 1998, p. 466). Results of this alternative model indicated no discernible evidence of random effects, so we continued analysis using the logit model without random effects.

The estimated model is statistically significant with a chi-square value of 711 and 8 degrees of freedom (Table 5). Most of the estimated coefficients are statistically significant at the 99% confidence level. The estimated coefficients for population density and Δpopulation density are positive, indicating that development has been more likely in areas where population density is higher and or growing faster. The estimated coefficient for gravity index is positive, indicating that development has been more likely with greater proximity to larger cities. The positive estimated coefficient for agriculture indicates that agricultural land in western Washington has been relatively more likely to be developed than forestland. The negative estimated coefficient for slope indicates that development has been less likely on steeper slopes. The positive estimated coefficient for elevation suggests that elevation may have a positive influence on development likelihood; however, the coefficient is not statistically significant at a high confidence level ($P = 0.19$). The positive estimated coefficient for time period indicates that development has been more likely from 1996 to 2004 than from 1988 to 1996 after controlling for other factors. The positive and statistically significant coefficient for spatial lag indicates that spatial autocorrelation likely is present; however, given the exploratory nature of our analysis, we have made no attempt to correct for it.

The signs and statistical significance of the estimated coefficients are consistent with the findings of other studies that have examined the socioeconomic drivers of forest and agricultural land development at fine spatial scales in the Pacific Northwest (e.g., Kline and Alig 1999, Kline et al. 2001, Kline 2003, Kline et al. 2003, Kline et al. 2007). From this we can surmise that the development process described by the data seems fairly reasonable. Although this would imply that the empirical model is useful for providing a reasonable depiction of forest and agricultural development, such as through projections of future development, the accuracy of projections based on the estimated model will be influenced by errors within the data on which the empirical model is based. That is, any errors in the satellite imagery–based land use classifications for sample points used in the analysis will carry forward in projections. Although caution clearly is warranted with these or any projections, it is worth noting that land use data and analysis typically involves making tradeoffs between data quality and availability, especially at finer spatial scales (Kline 2003, p. 113).

Projecting Future Development

One interest of policymakers and managers concerned about forestland development is anticipating where future development is most likely to happen. A common use of econometric models describing development at fine spatial scales is to forecast (or project) future rates and patterns of development. Projections of potential future development for 8-year time steps can be computed using the estimated model coefficients based on projected values of future population densities, changes in densities, and city populations used in the gravity index. Computed probabilities for individual 8-year time steps can also be combined to describe development probabilities for multiple 8-year time steps. To illustrate, we computed the combined probability of conversion from our base year of 2004 to 2020 as

$$prob(\text{DEVELOP}_{2004\text{ to }2020}) = prob(\text{DEVELOP}_{2004\text{ to }2012}) + [(1 - prob(\text{DEVELOP}_{2004\text{ to }2012})) \cdot prob(\text{DEVELOP}_{2012\text{ to }2020})],$$

in which the development probability for the 2012–2020 portion of the 2004–2020 projection depends on the probability that land remains undeveloped from 2004–2012.

The inclusion of the spatial lag variable in the full model (Table 5) complicates projection because future values for the spatial lag variable are unknown. Currently, no simple and universally accepted method exists for addressing how to deal with spatial lag variables when using econometric models to compute predicted (or projected) values. For this reason, we re-estimated the econometric model omitting both the spatial lag and time period variables to ease projection computation. The estimated coefficients for this simplified model are very close in magnitude and statistical significance to those of the full model (Table 5). We used a straight-line extrapolation of population growth reported by the US Census Bureau (1990–2000). We converted the computed 2004–2020 development probabilities into categorical ranges and focused our illustration on the greater Seattle area (Figure 1). The map of likely future development indicates the degree of development likelihood on land in the region given its proximity to existing urban areas, location along major transportation corridors extending from them, existing land uses, and topographic characteristics. If combined with additional analysis of development impacts on the management of remaining forestland (e.g., Kline et al. 2004), such maps could enable policymakers and managers to anticipate where forest management focused on timber and commodity production is most likely in the future.

The regionwide aggregate expected areas of different land types projected to be developed by 2020 can be computed by multiplying pixel-level predicted development probabilities by 2004 pixel areas and summing up for the western Washington region (Table 6). These estimates suggest that nearly 128,000 ac of wildland forest and other forestland are likely to be developed by 2020, for a weighted average probability of development of about 2%. This rate is fairly comparable to projections made by other studies using different data and methods and summarized by Alig and White (2007). Alig and White (2007), for example, project an 8% loss of nonfederal forestland to development over a longer projection period 1997–2027. They also report other projections of 4% and 13% made by Adams et al. (1994) and Alig and Plantinga (2004), respectively, for the period 1997–2025. Our estimates suggest that the aggregate expected area of developed land will increase by about 350,000 ac from 2004 to 2020, or about 30% (Table 6). This development rate is quite a bit less than the lowest rate reported by any of the other studies reviewed by Alig and White (2007), which ranged from a 60% increase for 2000–2020 estimated by Nowak and Walton (2005) to a 120% increase estimated by Alig et al. (2004) for 1997–2027. Studies that found projections in between are Theobald (2005) with 70% for 2000–2020, Alig and White (2007) with 100% for 2007–2027, and Alig and Plantinga (2004) with 110% for 1997–2020.

Differences among studies are to be expected given that they each use different land use definitions, data, methods, and projection periods. In our study, for example, the relatively low estimate of the percentage increase in developed land might arise in part from our inclusive definition of development—including low-density development along with urban land—which caused our 2004-based area of developed land to be largest of all existing studies. That, along with the shorter projection period (2004–2020) likely contributed to decreasing our development rate projection relative to those of other studies when expressed in percentage terms. Another difference is the finer spatial scale at which our study was carried out. The studies of Alig et al. (2004), Alig and Plantinga (2004), and Alig and

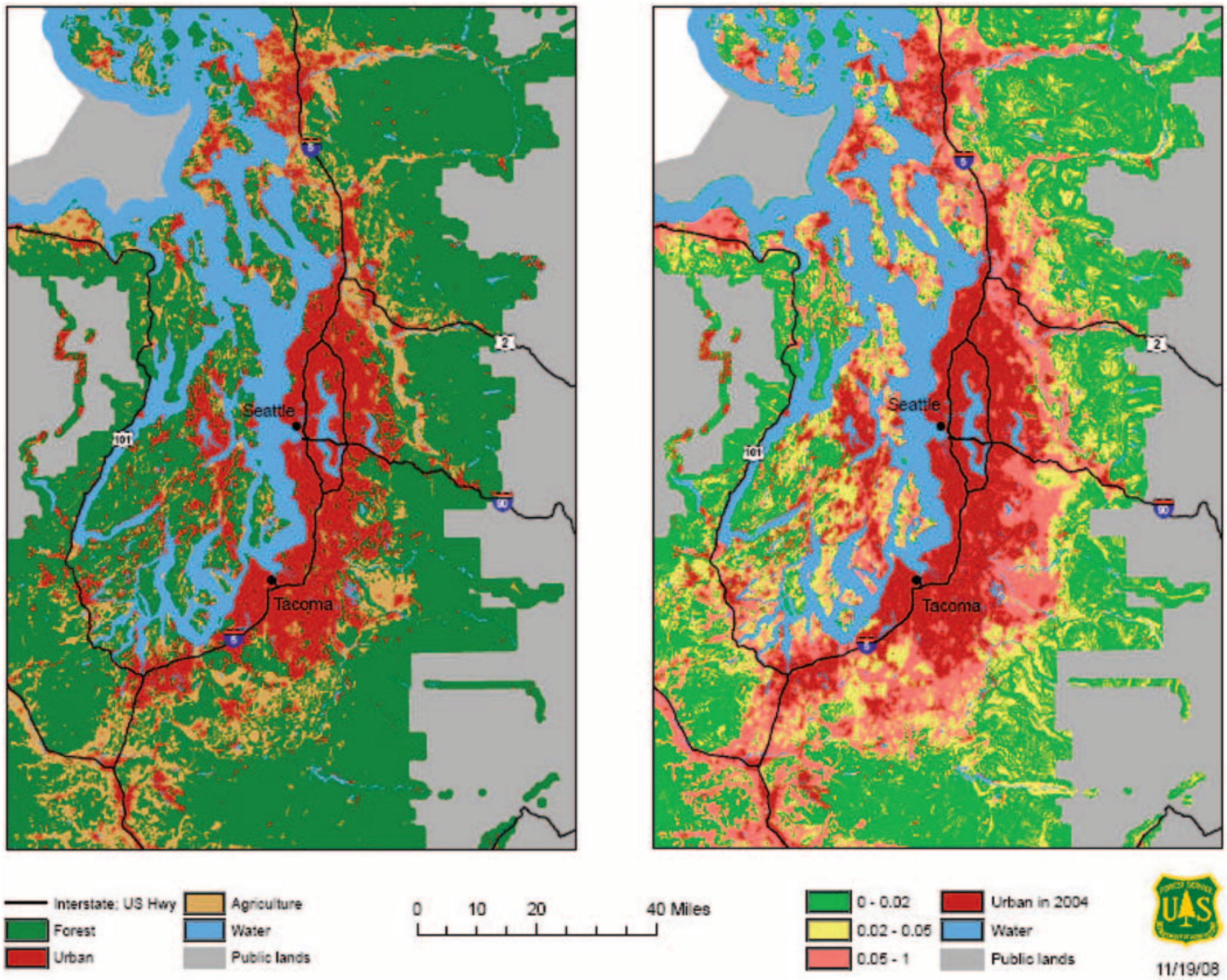

Figure 1. Satellite imagery–based 2004 land use and model-predicted probability of development by 2020.

Table 6. Satellite imagery–based 2004 land use and model-predicted expected area of land lost to development by 2020, by land use class, for nonfederal land in western Washington.[a]

Land use	Acres (in thousands) in 2004[b]	Weighted average probability of development by 2020	Expected area of land lost to development	Forecast acres (in thousands) in 2020
Wildland forest	6,165	0.014	86	6,079
Other forest	909	0.044	40	869
Intensive Agriculture	519	0.092	48	471
Mixed agriculture	1,087	0.163	177	910
Developed	1,178			1,529

[a] Estimated using estimated coefficients of the simplified model from Table 5.
[b] Acres reported by Rural Technology Initiative (2006, p. 20).

White (2007), for example, are all based on county-level data describing the proportions of counties in particular land uses. Land use analyses based on county-level data may not enable full consideration of the effects that local topographic (e.g., slope), transportation, and other factors have on constraining or motivating development in particular locations.

Conclusions and Implications

The purpose of this study was to evaluate the accuracy and usefulness of land use data gathered for western Washington using an automated process for interpreting satellite imagery. That FIA-funded, earnest data gathering effort sought to develop data similar to what FIA already gathers for Oregon using "eyes-on" interpretation of high-resolution digital aerial photos. From our assessment, we conclude that automated satellite imagery processing as outlined in Rural Technology Initiative (2006) yielded land use data that are useful for identifying those lands most likely to remain available for timber production but less useful for correctly locating forestlands in developing areas. A primary concern is the potential misclassification of agricultural lands as forest and vice versa. The satellite imagery–based data also under-identify small pockets of development, as well as areas characteristic of fairly low-density development, possibly because these forms of development are most readily obscured by tree cover or misinterpreted as tree cover. This under-identification would be particularly problematic in land use data applications focused on evaluating the potential adverse effects of parcelization on private forest management and forest fragmentation on the provision of amenities and other ecosystem services. Preliminary analysis suggests that the data are useful for econometric analysis of past forest and agricultural land development and for forecasting potential future development, particularly if such uses are intended primarily to provide a general representation of future land use change—to support landscape simulation, for example—rather than to provide a precise land use inventory.

Altogether, we feel that automated processes for interpreting satellite imagery (e.g., Rural Technology Initiative 2006) do offer some promise for providing useful land use information, particularly when policy and management interests center on identifying large tracts of relatively undeveloped forestland. However, given the increasing availability of high-resolution digital aerial photos such as those used by FIA in Oregon (Lettman 2002, 2004) and increasing interest in identifying low-density forestland development, we recommend using satellite imagery in place of aerial photo interpretation only when it is substantially cost-competitive. In this case, the costs involved in developing and executing the automated satellite imagery processing methods in western Washington were not all that different from the costs incurred from aerial photo interpretation in western Oregon. Although the costs of future data gathering in western Washington now might be lower should analysts be able to repeat existing automated processes with future satellite imagery, potential cost savings arguably may not outweigh the apparent loss of accuracy resulting from the application of an automated process. This conclusion contributed to the FIA program's recent decision to invest in developing new land use data for Washington using the aerial photo interpretation methods outlined in Lettman (2002, 2004).

More generally, although photo interpretation of aerial photos can involve interpreter bias arising from differences in the way individual photo interpreters observe and record land uses, automated processes can also result in bias if processing algorithms systematically misclassify particular land uses. An advantage of photo interpretation over an automated process appears to be the greater opportunity for subjective judgment by the interpreter, enabling greater quality control during the data gathering process. Should land use analysts opt for using satellite imagery, we advise great care in devising processing procedures focused on distinguishing between forest and agricultural lands and identifying low-density development or small developed areas within forest tracts. Given that other land use analysts (e.g., Irwin and Bockstael 2007, p. 20675) have expressed similar concerns about satellite imagery–based land use data—specifically, the National Land Cover Database—forestry officials may want to carefully explore and weigh their options regarding how best to procure land use data for examining land use patterns and trends and their implications for forestry.

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