Using Landsat Imagery and FIA Data to Examine Wood Supply Uncertainty

Curtis A. Collins[1] and Ruth C. Seawell[2]

Abstract: *As members of the forest products industry continue to reduce their landholdings, monitoring reliable future timber supplies becomes an increasingly important issue. This issue requires both spatial and forest inventory information to meet the strategic planning needs of these entities. Increased depth in the archival span of imagery available from the Landsat program in conjunction with timber estimates from FIA data have been used by Larson and McGowin, Inc. to fill this information gap in the southern U.S. by further refining timber supply projections.*

In generating this information for various clients, Landsat MSS and TM (including ETM+) data have been used to create forest age and type maps with temporal origins as early as 1972 to as recent as 2007. By using forest type and age layers, spatial products can be created that have matching attributes to those presented by FIA. In doing so, FIA volumes can be adjusted to generate expected total volumes for regions by using the remotely sensed/image processed type and age acreages. Once volumes by type and age classes are established, the SubRegional Timber Supply (SRTS) model can be use to analyze supply/demand relationships between multiple products, endogenous land use, varying growth and yield components and regional and local demand estimates.

Results from a sampling of these projects will be presented in such a way as to share image processed accuracies and overall project results. Special attention will be given to the nature of the results and how our clients have found them helpful. Examples will also be presented showing how the integration of GIS operations can be utilized along with the spatial data product to glean further results that are more widely applicable.

Keywords: Landsat, change detection, SRTS, supply, remote sensing.

Introduction

With the large-scale shift of private forest ownership in the U.S. ongoing, many changes are occurring as public and private entities adapt to answer evolving problems. One obvious problem with the ownership shift is noted in the

[1]Larson and McGowin Forestry Consultants, P.O. Box 230, Watkinsville, Georgia 30677, ccollins@larsonmcgowin.com
[2]Larson and McGowin Forestry Consultants, P.O. Box 2143, Mobile, Alabama 36652, rseawell@larsonmcgowin.com

reduction of integrated land holding entities within organizations that consume wood and timber. With no more company lands, procurement personal are quickly adapting to rely heavily on outside sources of material that, in some cases, were marginalized in the past. One developing tool of importance to many of these procurement personnel involves wood basin analysis where regional mill consumption basin(s) are identified and analyzed to yield information for strategic planning purposes.

Use of these techniques and resulting information is not new. While many mills are having reliable company land bases removed from the equation, some have been successfully operating without these holdings for some time. In doing so, these firms relied on forest analysts to monitor supply/demand trends at the multiple scales, not the least of which being the basin from which a mill of interest relied upon for raw material. Uses of FIA data and reports were paramount in performing these analyses, but many users, knowing the limitations of FIA, desired additional information and at finer scales, temporally and spatially, than FIA intended.

One way where FIA data accentuation was explored and achieved involved the most successful space-borne remotes sensing program, the Landsat program, which gives the public access to data from 1972 to the present. Using this large bank of data, FIA results could be updated in longer lag periods between field measurement periods. This data could also be used to accentuate or even replace age class estimates as FIA is a sampling approach that, in smaller areas in particular, may not yield as accurate results as Landsat-based products. Similarly, Landsat data can be used to map broad forest type classes which, again, could be used to crudely update or replace FIA forest type area estimates.

With FIA and Landsat estimates in hand, various approaches can be taken to yield viable supply/demand/consumption information that can be used to analyze regional timber supply situations as well as inform existing timber supply models. The widely adopted SubRegional Timber Supply (SRTS) model is one such model that was developed to examine southern timber markets (Abt *et al.*, 2000), and has been applied both in the southern and northern U.S. to examine timber supply and prices. Over the last five years, SRTS' capability has expanded to include the analysis of multiple products, as well as endogenous land use and the integration of growth and yield components and regional/local demand estimates. The model provides ending inventories, annual removals, and price indices for the analysis of future timber supply scenarios.

Methodology

Landsat Data and Analyses

With the launch of Landsat 1 on July 23, 1972, the U.S. embarked on a program that has and continues to yield continuous and comprehensive earth surface science information for various mapping projects. The data yielded from

this ongoing program includes Multispectral Scanner System (MSS) data with ~60m resolution data in visible green, visible red, near-infrared (NIR), and mid-infrared (MIR) bands; Thematic Mapper (TM) data with ~30m resolution data in visible blue, visible green, visible red, near-infrared (NIR), and two mid-infrared (MIR) bands; and Enhanced Thematic Mapper+ (ETM+) data with the same capabilities as TM data plus a ~15m panchromatic layer covering 0.52-0.9 μm. For the purpose of this paper, these data were used in two analyses: forest age mapping and forest type mapping.

The forest age mapping approach used by Larson and McGowin currently utilizes a post-classification comparison approach (similar to Collins *et al.*, 2005). In this methodology, a current forest/non-forest map, usually derived from unsupervised classification techniques and interpretation, is manipulated in descending years through a temporal dataset of derived "cut" layers until each forested pixel is tagged with a year of origin, unless this origin is beyond the scope of Landsat (earlier than 1972). Similarly, a harvest layer was built by ascending, again using cut layers, from a forest/non-forest layer that was ~10 years old, using the forest class, to the current forest/non-forest layer, using the non-forest class.

The age determination process is designed to detect clearcut areas, not partial harvest or thinning operations. However, if these partial harvests or thins are heavy enough they may trigger an origin set inappropriately. With regards to temporal resolution, datasets are targeted to be acquired from every 1 to 5 years usually throughout the span of Landsat data (usually 1972-1973, depending on data quality) depending on site and growing conditions. It is also worth noting that while leaf-off data, data collected after deciduous leaf senescence has occurred, can be useful in this process; leaf-on data is targeted as it typically better discriminates forest from non-forest. The creation of cut layers from individual Landsat images from the temporal dataset is usually done through independent unsupervised classification or applying image thresholds using a variety of image transforms incorporating individual Landsat bands and/or Normalized Difference Moisture Index (NDMI) and/or Normalized Difference Vegetation Index (NDVI).

The forest type mapping approach uses the same current forest/non-forest layer to mask out non-forest pixels. In the remaining forested areas, a current Landsat leaf-off dataset is acquired. This dataset is next either passed through an unsupervised classification and interpretation routine or interpreted for and classes via NDVI thresholds in order to derive deciduous (usually hardwood), evergreen (usually softwood), and mixed deciduous-evergreen classes.

Timber Supply Analyses with SRTS

Traditionally, USFS FIA periodic inventories have been the data source for the SRTS model. However, because of the increasing age between FIA surveys and

dramatic shifts in harvest patterns, remote sensing-based classification and change detection techniques for forest timber types have been used as a means to update these estimates as well as to refine FIA area assessments. Typically, the area estimates by broad timber types and five-year age classes are used in conjunction with FIA per-acre estimates to derive timber inventories.

While the inventories in the study basins may not necessarily be too old for timber supply assessment, there could exist some conditions that merit an update using satellite imagery. Dramatic shifts in harvest patterns since the FIA survey or damage activities like hurricanes, ice storms, insect infestation, etc., can be detected in a satellite update. Also, permanent losses in timberland due to urbanization can be measured and trends observed. Finally, the satellite image area assessment is oftentimes a more accurate estimate of the area than the FIA estimates.

In the previous versions of the SRTS model, harvests were held constant, sometimes creating unrealistic price projections. In this "harvest" mode the annual harvest levels input by the user are assumed constant and harvest does not react to higher or lower prices. Because of that the model can only adjust the price needed to achieve the desired harvest given the inventory levels thus creating what appear at times unrealistic price trends.

The latest version, MP SRTS, now allows users to specify a demand curve to find the equilibrium solution between supply and price. Demand is modeled at the aggregate level; however, through the inventory shifts by product, region and owner, a solution for equilibrium price simultaneously determines harvest shifts across regions and owners. Demand can either be held constant as in a harvest run or increased through time. The goal program then harvests across management types and age classes to get the projected target mix, while harvesting consistently with historical harvests for the region. The difference is that harvest and price react to the change in demand. The effect of an increasing demand on harvest and price depends on the supply, i.e. inventory. Other things being equal, an increase in demand will raise price and harvest; but harvest will not increase proportionately since the price increase dampens some of the harvest.

Results and Discussion

Landsat Data and Analyses

One set of resulting Landsat classifications were compared to client provided stand data in order to get a notion, albeit not definitive, with regard to accuracy for a specific project. The data and client were situated in the southeastern U.S. The client provided stand data came in the form of a polygon vector layer with each delineated stand attributed with management species composition (usually a target management composition, not necessary what was present), age (actually year of establishment), and size (acres). The data was last updated in June 2006

and covered approximately 400,000 acres of land being actively managed for loblolly pine (*Pinus taeda*). After receiving the data, it was cleaned to better match existing GIS stand types, mainly from the management composition field, with the Landsat derived classifications.

In cleaning the data, the management classes were re-classed to better match the deciduous/hardwood, evergreen/pine, and mixed forest classes as well as open (there were some fields and wildlife foodplots) and harvest non-forest classes. In addition to these classes, this cleanup also used observed histogram data to note that rather consistent forest type given age distributions were heavily, and inappropriately, favoring the deciduous type in the youngest age classes (Figure 1). For this reason, young forested areas were stripped of a class designation and assigned as a "regeneration" class. These data were next overlaid on overlapping forest age and type layers, created with current data from 2007, with zonal attributes being calculated so as to indicate the majority type and age of each stand with respect to the two classified products. The observed age attributed to the stands and the zonal extracted ages were then rescaled to 5 year age classes to better match an FIA matching scenario.

Figure 1. The distribution of proportion of forest type within six younger age classes shown in forest type bundles.
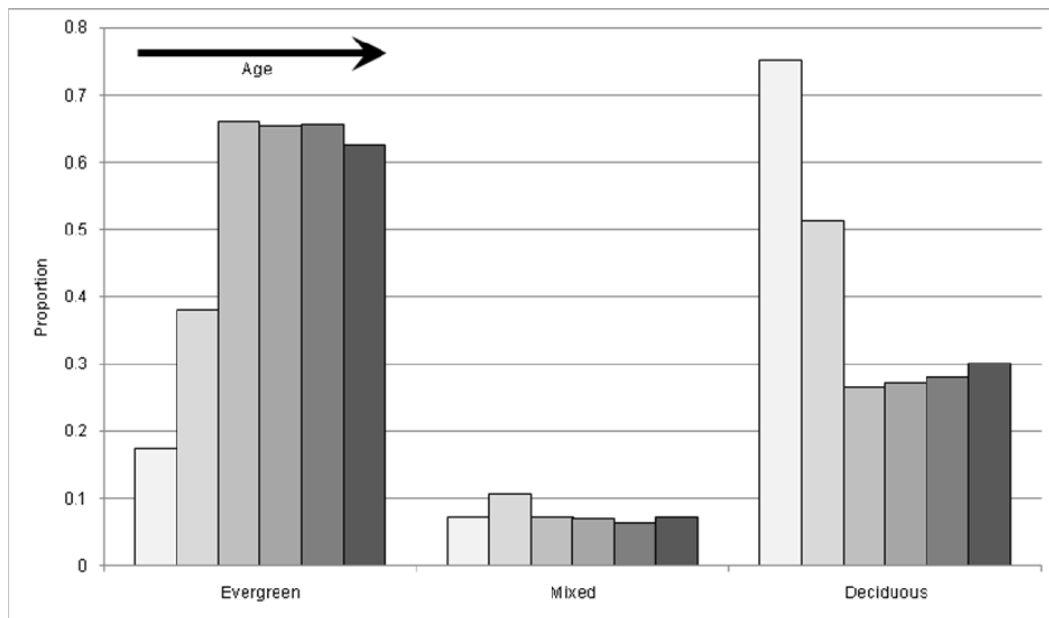
With types and ages scaled to similar classes, the acreages in each stand were assigned to the appropriate age and type error matrix cells as indicated in Tables 1 and 2, respectively. The resulting two error matrices illustrate results from a process that, using these test data, performs well in the age determination aspect and below expected in the forest type classification aspect.

Table 1: Age comparison (error matrix) by stand polygons (acres), making sure only to compare ages in stands noted as forested stand layer

Classified Landsat Data

		0-5	6-10	11-15	16-20	21-25	26-30	31-35	> 35	
	0-5	**56,707**	9,248	53.9	52.7	449.1	274.3	251.5	709	67,744
	6-10	16,708	**53,933**	1,744	8.4	9.6	77.8	1146.1	2,219	75,847
Reference Data	11-15	8.4	14,544	**20,608**	262.3	8.4	33.5	6	2,859	38,329
	16-20	316.2	673.1	8,532	**16,768**	796.4	28.7	34.7	4,278	31,425
	21-25	2,238	1,814	16.8	3,353	**9,513**	162.9	58.7	1,628	18,786
	26-30	1,943	1,569	2.4	25.1	725.7	**2,529**	326.9	2,562	9,681
	31-35	789.2	959.3	13.2	13.2	2.4	232.3	**1,266**	942.5	4,219
	> 35	6,224	7,921	1,720	1,402	1,965	3,965	2,905	**106,807**	132,910
		84,933	90,661	32,690	21,886	13,471	7,304	5,996	122,002	**378,941**

	Percent	psKHAT
Overall %	71%	63%

Table 2: Type comparison (error matrix) by stand polygons (acres)

Classified Landsat Data

		Harvest	Regen	Open	Pine	Mixed	Hdwd	
	Harvest	**3,853**	5,702	5,497	4,465	4,970	13,344	37,830
Reference Data	Regen	31,432	**78,338**	10,158	1,529	713.8	1,635	123,806
	Open	35.9	704.2	**3,917**	257.5	470.7	1039.5	6,424
	Pine	480.2	18,431	6,149	**75,162**	5,739	2,638	108,599
	Mixed	445.5	2,047	268.3	4,361	**23,674**	396.4	31,193
	Hdwd	358.1	5,927	1,309	7,020	9,078	**66,713**	90,406
		36,606	111,150	27,298	92,793	44,646	85,767	**398,258**

	Percent	psKHAT
Overall %	63%	53%

Note that the age results in Table 1 show a fairly good overall agreement at 71% with a pseudo-Kappa-hat of 63% (this is a pseudo measure as penalizing chance agreement, which is the goal of the Kappa statistic, assumes certain sample allocation practices that were not employed in this loblolly management-focused forestland ownership test data). In further analyzing the data, it was noted that the age classification process seemed to have a bias so that regenerated forests were being assigned an age of zero even after they had already been regenerated (Figure 2). This was first noted in the elevated off diagonal cells in the Table 1 error matrix (highlighted in gray) where large area amounts were noted in younger classified classes than observed.

Figure 2. The distribution areas, in acres, of age bias (observed minus classified), in one year age bias classes, for the forested stands in the polygon vector test dataset.
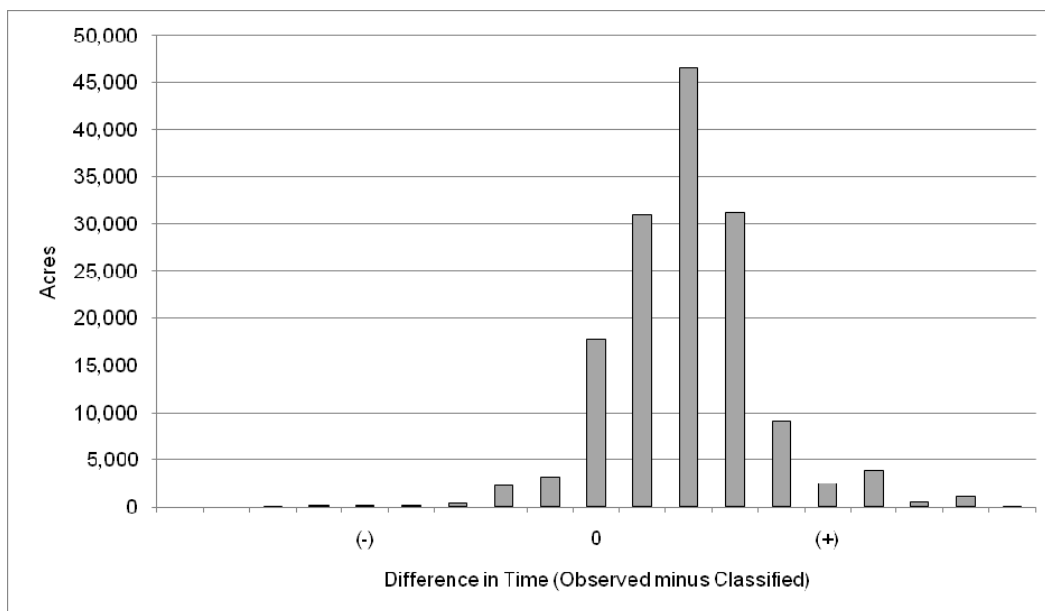
With regard to the type classification (Table 2), the results were below expected at 63% overall agreement with a pseudo-Kappa-hat of 53%. These poor results, however, can be refined if the regeneration and harvest classes, which are very close in meaning, are merged (new diagonal matrix value derived from gray shaded area), yielding a refined overall agreement proportion of 73%. Further refinement involving only looking at the forested stands (the error matrix region with individual cells bordered) reveals an overall agreement of 72%. Aside from these results, it is worth echoing the previous statement involving the nature of the stand data itself. This problematic nature is primarily focused on the management species attribute field, which again, is sometimes a management target as opposed to what is actually present, and the one year age difference between the stand data (last updated in June 2006) and the classification (based off of leaf-on Landsat data from 2007). Also, this data, again, is biased toward actively managed loblolly pine plantations, thus, it is not representative of the wood basin as a whole.

Timber Supply Analyses with SRTS

Because most regional southern timber supply analyses focus significantly on pine plantation availability, the forest type accuracy bias toward pine in the satellite classification processes is not as restrictive as it might be if supply was equally influenced by other forest types. Likewise timely and improved updates of regeneration and harvest classes can provide more critical information than improved allocation of five year age classes through time in the SRTS model. In other words it is more important to know how many acres are cut and planted in a given period than the exact age class distribution of them through time when projecting future supply.

7

However, because of the difficultly in distinguishing between "regenerating" or "harvested" classes these two forest types were combined in their age class group and the average forest type ratios between pine, hardwood and mix for the age classes 5-15 were used to allocate their "type". In essence this assumes that the reforestation trends of the last fifteen years are still applicable. This may or may not be the case. This includes acres that were "changed" or "harvested" but that are not designated as timberland yet either. Similarly, because of the age of the Landsat data, the oldest age class able to be determined by the satellite classification is 30-35. Because the SRTS model utilizes the FIA inventory five year age classes up to 50, the FIA age class proportions are used to allocate the satellite acres accordingly for the 35 and older group.

The SRTS model uses FIA's five broad management types as well as two ownership groupings: corporate and private. Because the satellite classification can only distinguish "forest cover types", assumptions must be made to allocate these three forest cover types (pine, mix and hardwood) into the five FIA/SRTS management types (pine plantation, natural pine, mix/hardwood, upland hardwood, and bottomland hardwood). In the above client dataset the satellite classification estimated 3% more overall timberland acres than was provided in the SRTS inventory data files. The allocation of the satellite acres after adjustment for the age class 0-5 was 49% pine, 11% mix, and 39% hardwood. This compares to a SRTS allocation of 44% pine, 11% mix and 44% hardwood. The SRTS percentages between planted and natural pine and upland and bottomland hardwood were used to further allocate the satellite pine and hardwood acres within their age class groupings (Table 3).

Table 3: A comparison of the original FIA/SRTS acreage allocation to adjusted (using FIA/SRTS ratios/proportions) classified satellite acreages.

FIA/SRTS Type and Age Area Estimates

Age Class	Planted Pine	Natural Pine	Mix	Upland Hardwood	Bottom Hardwood	Grand Total
0-5	62,860	89,796	46,119	280,600	39,229	638,364
6-10	220,595	91,612	70,710	174,317	22,301	579,535
11-15	200,117	129,937	66,582	135,369	30,184	562,189
16-20	251,314	99,511	50,647	82,960	14,699	499,132
21-25	299,795	108,334	60,949	94,566	17,123	580,768
26-30	181,636	133,447	51,426	81,831	34,849	483,189
31-35	74,105	90,762	67,053	89,498	18,976	340,394
36-40	26,366	66,588	54,538	129,572	51,416	328,480
41-45	17,055	103,187	60,024	118,759	26,138	325,163
46-50	0	75,502	42,169	177,677	14,919	310,266
>50	0	219,328	92,723	842,904	223,950	1,378,905
Total	1,453,605	1,208,004	662,939	2,208,055	493,783	6,026,386
% Total	24%	20%	11%	37%	8%	

Adjusted Satellite Classified Type and Age Area Estimates

Age Class	Planted Pine	Natural Pine	Mix	Upland Hardwood	Bottom Hardwood	Grand Total
0-5	192,684	94,745	46,085	110,605	15,462	459,581
6-10	360,629	149,768	83,286	198,435	25,386	817,503
11-15	250,703	162,782	60,705	139,119	31,020	644,329
16-20	267,847	106,057	65,866	148,978	26,396	615,144
21-25	301,960	109,116	36,765	82,437	14,927	545,206
26-30	89,441	65,711	44,299	107,317	45,703	352,472
31-35	42,965	52,622	31,829	116,709	24,746	268,871
36-40	43,462	109,764	65,677	113,660	45,102	377,666
41-45	28,114	170,095	72,283	104,175	22,928	397,594
46-50	0	124,459	50,781	155,857	13,086	344,183
>50	0	361,544	111,661	739,390	196,448	1,409,042
Total	1,577,805	1,506,662	669,236	2,016,681	461,205	6,231,589
% Total	25%	24%	11%	32%	7%	

Using the FIA per acre averages with the new satellite acres a revised inventory can then be used in the SRTS model runs. Likewise additional spatial constraints such as SMZ or slope restrictions, urban growth projections, transportation limitations can be derived to be used in conjunction with availability or sensitivity analysis. Figure 3 compares the growth/removal ratios for such a sensitivity analysis looking at harvest increase, land loss assumptions and increased federal land supply.

Figure 3: Growth and removal rates for a test wood basin of interest using various scenarios for sensitivity analysis purposes.
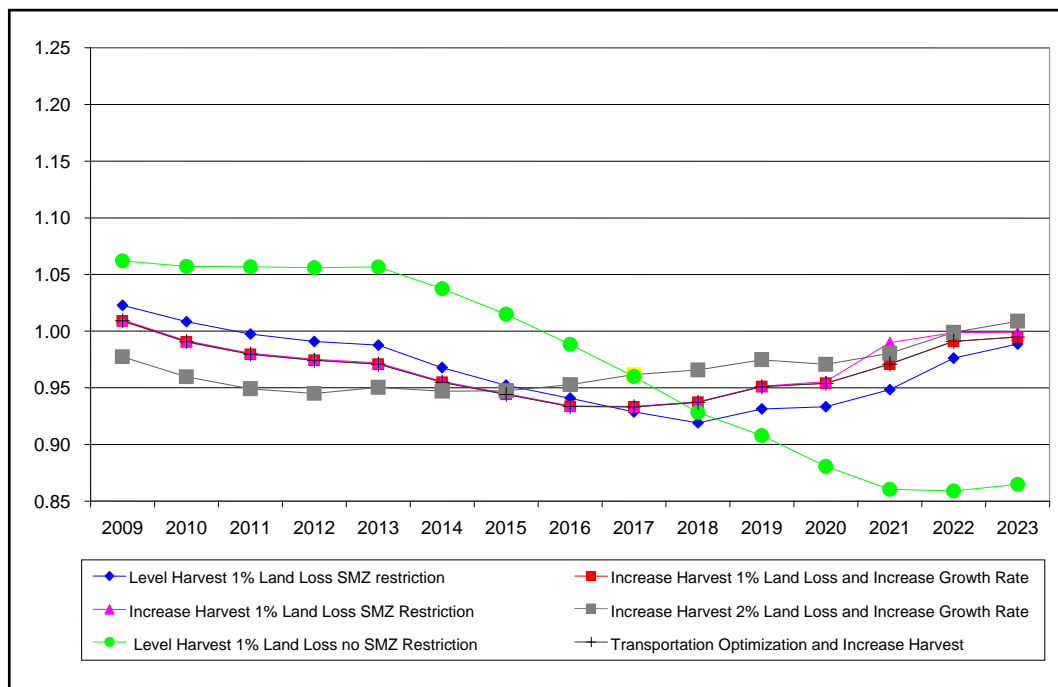
Conclusions

With regard to overall project performance there is still, as always, room for improvement. When the practices of application and science meet, compromises are usually made, as was the case here. Had more time been available, the results could have been further refined and, as one might expect, the accuracy of the products would have been improved. With this said, from a remote sensing aspect, lessons from this process include thrusts to improve efficiency; reduce costs (which is tied to efficiency of course); address bias in classified age; examine the classification of forest types at varying ages, removing the trend to over-classify the deciduous type in younger classes; and generally work to better align classified products with FIA data. These improved classification techniques in conjunction with improved application of per acre inventory averages and growth rates should help to provide inventory estimates that are more reflective of current market conditions for SRTS model runs. Likewise, because spatial analysis is available using the classification and its classed acreage distribution, sensitivity analysis can also be more reflective of future market scenarios improving strategic forest planning opportunities.

References

Collins, C.A., D.W. Wilkinson, D.L. Evans. 2005. Multi-temporal analysis of Landsat data to determine forest age classes for the Mississippi statewide forest inventory-preliminary results, pp. 10-14. In Proceedings of the 2005 International Workshop on the Analysis of Multi-Temporal Remote Sensing Images. [CD-ROM]; 2005 May 16-18; Biloxi, MS.

Abt, R.C., F.W. Cubbage, G. Pacheco. 2000. Southern Forest Resource Assessment Using the SubRegional Timber Supply (SRTS) Model. Forest Products Journal. 50(4).