A Method for Partitioning Total Leaf Area Index into Overstory and Understory Strata for Distributed Hydrologic Modeling based on Forest Inventory, Remote Sensing, and Biophysical Data

Sara A. Goeking, Biological Scientist, USDA Forest Service, Ogden, UT, sgoeking@fs.fed.us
David G. Tarboton, Professor, Dept. of Civil and Environmental Engineering, Utah State University, Logan, UT, dtarb@usu.edu

Extended Abstract

Recent tree mortality across the western US has led to numerous investigations of the relationship between forest disturbance, snow accumulation and ablation, and runoff. Although historical studies suggested that recent forest disturbances would lead to increased runoff (Andréassian 2004; Bosch and Hewlett 1982; Troendle 1983), in recent studies on the effects of insect-caused tree mortality on runoff, this expectation was not met (Biederman et al. 2015; Slinski et al. 2016). Further, several studies have found that forest density and structure can affect snow accumulation and melt rates either positively or negatively (Ellis et al. 2011; Harpold et al. 2014; Lundquist et al. 2013). To better understand the mechanisms that determine whether forest disturbance will lead to increased snowpack and runoff, distributed hydrologic models require accurate representations of forest density and structure at sufficiently fine resolution to detect disturbances (Andréassian 2004). Several existing distributed hydrologic models, such as the Regional Hydro-Ecological Simulation System (RHESSys; Tague and Band 204) and the Distributed Hydrology-Soil-Vegetation Model (DHSVM; WIgmosta et al. 1994), are capable of representing overstory versus understory canopy strata in terms of leaf area index. Leaf area index, or LAI, is a dimensionless quantity that represents the one-sided surface area of all leaves within a given ground area divided by that ground area. However, most existing LAI datasets are based on remote sensing (e.g., Xiao et al. 2013), and do not distinguish overstory from understory LAI. Thus, most applications of distributed hydrologic models represent vegetation in terms of total LAI rather than separate overstory versus understory layers. The ability to use distributed hydrologic models to enhance our understanding of the link between forest disturbance and water resources requires distinction of overstory versus understory LAI.

This paper describes the development of a new spatially explicit dataset of overstory and understory LAI. We used forest inventory data to estimate overstory and understory LAI at the plot scale, and then applied a statistical learning algorithm to produce spatially gridded overstory and understory LAI by combining the plot-level LAI estimates, remote sensing, and biophysical predictors. Forest inventory data were collected by the USDA Forest Service's Forest Inventory and Analysis (FIA) program (Burrill et al. 2017; USDA 2013), which measures permanent plots with a mean spacing of about 5 km and a re-measurement period of 10 years or less, throughout all ownerships and forest types of the United States. Although FIA

measurements do not include LAI, they do include the depth and density of understory and overstory vegetation. Using this information, we partitioned remote sensing-based estimates of LAI into overstory versus understory components. Remote sensing LAI data were obtained from Moderate Resolution Imaging Spectrometer (MODIS) satellite data at 500 m resolution; see Xiao et al. (2013) for more information on MODIS and the LAI dataset. The plot-based estimates of overstory LAI were entered into a random forests model (Breiman 2001), with remote sensing, climate, and topographic data as predictors (Table 1).

Table 1. Predictor variables, as well as their sources and citations, that were included in the random forests models for producing spatially gridded overstory and understory leaf area index (LAI)

Predictor variables	***Source***	***Citation***
Elevation (DEM)	The National Map	NA
Slope	DEM/ArcGIS Pro function	NA
Folded aspect	DEM/ArcGIS Raster Calculator	McCune and Keon (2002)
Solar radiation index	DEM/ArcGIS Raster Calculator	McCune and Keon (2002)
Topographic wetness index	DEM/TauDEM	http://hydrology.usu.edu/taudem/
Slope:area ratio	DEM/TauDEM	http://hydrology.usu.edu/taudem/
Distance up to ridge	DEM/TauDEM	Tesfa et al. (2011)
Distance down to stream	DEM/TauDEM	Tesfa et al. (2011)
Mean annual precipitation[1]	http://www.prism.oregonstate.edu	Daly et al. (2000)
Maximum annual temperature[1]	http://www.prism.oregonstate.edu	Daly et al. (2000)
Minimum annual temperature[1]	http://www.prism.oregonstate.edu	Daly et al. (2000)
STATSGO soil map units	http://websoilsurvey.nrcs.usda.gov	NA
NLCD cover classes	http://viewer.nationalmap.gov/viewer/	Homer et al. (2015)
NLCD tree canopy cover	http://geoinfo.msl.mt.gov/	Homer et al. (2015)
Mean NDVI of snow-free dates	http://www.ntsg.umt.edu/project/landsat/	Robinson et al. (2017)

[1]PRISM normals are based on the period 1981-2010 at 800 m resolution.

We developed and tested the model in the South Fork Flathead watershed of Montana (Figure 1). This watershed experience extensive tree mortality in recent decades due to a combination of insects, drought, wildfire, and disease. Therefore, we produced separate models for two time periods that represent pre- (2003-2009) and post-disturbance (2010-2016). We used package randomForests (Liaw and Wiener 2001) in the open-source statistical analysis program R (R Core Team 2018) to produce separate maps of overstory and understory LAI for the two time periods (Figure 2). The out-of-bag error rates for the two time periods were 0.13 and 0.10, respectively, where out-of-bag error is calculated as the mean error among multiple iterations of bootstrap aggregated (bagged) subsets of the data being sampled with replacement, withheld from model calibration, and then used for validation (Breiman 2001). Model R^2 values were 0.463 and 0.615, respectively, for the two time periods. Comparisons of overstory, understory, and total LAI for the two time periods indicated an overall decrease in LAI, which was expected given the recent disturbances in this watershed (Figure 3). Note that the locations of the greatest decrease in overstory LAI correspond to areas burned between the two periods (Figure 1).

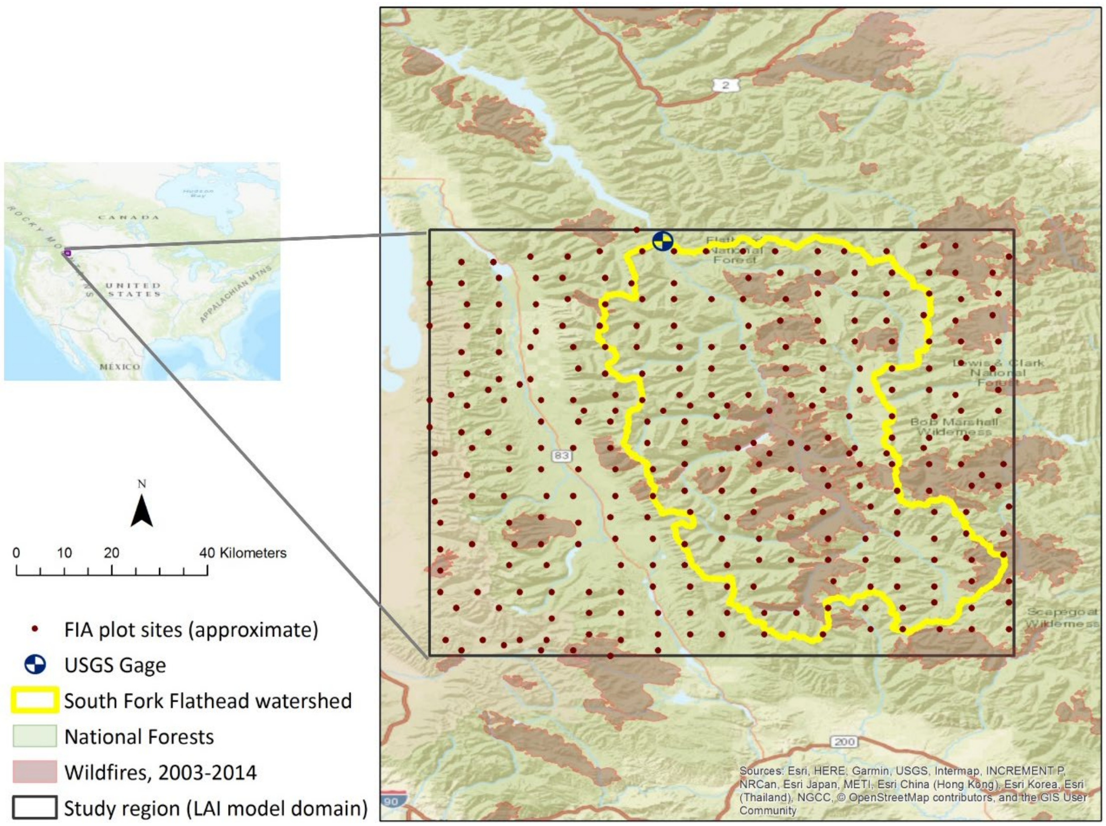

Figure 1. The South Fork Flathead watershed of northwestern Montana. Wildfire polygons were mapped by the Monitoring Trends in Burn Severity program (Eidenshink et al.2007).

The importance of this work is that it provides separate overstory versus understory LAI datasets and thus enables more precise assessment of the effects of widespread tree mortality and forest disturbance on hydrologic processes and water availability. The distinction of LAI strata capitalizes on the ability of existing distributed hydrologic models, several of which represent separate overstory and understory strata, to accurately represent the effects of forest disturbance. This capability will enable more accurate simulation of the various process-level responses, such as interception, radiation transmission, sublimation, and evapotranspiration, following forest disturbance. Therefore, it may lead to more accurate predictions of the net effect of forest disturbance on the partitioning of precipitation into runoff versus evapotranspiration.

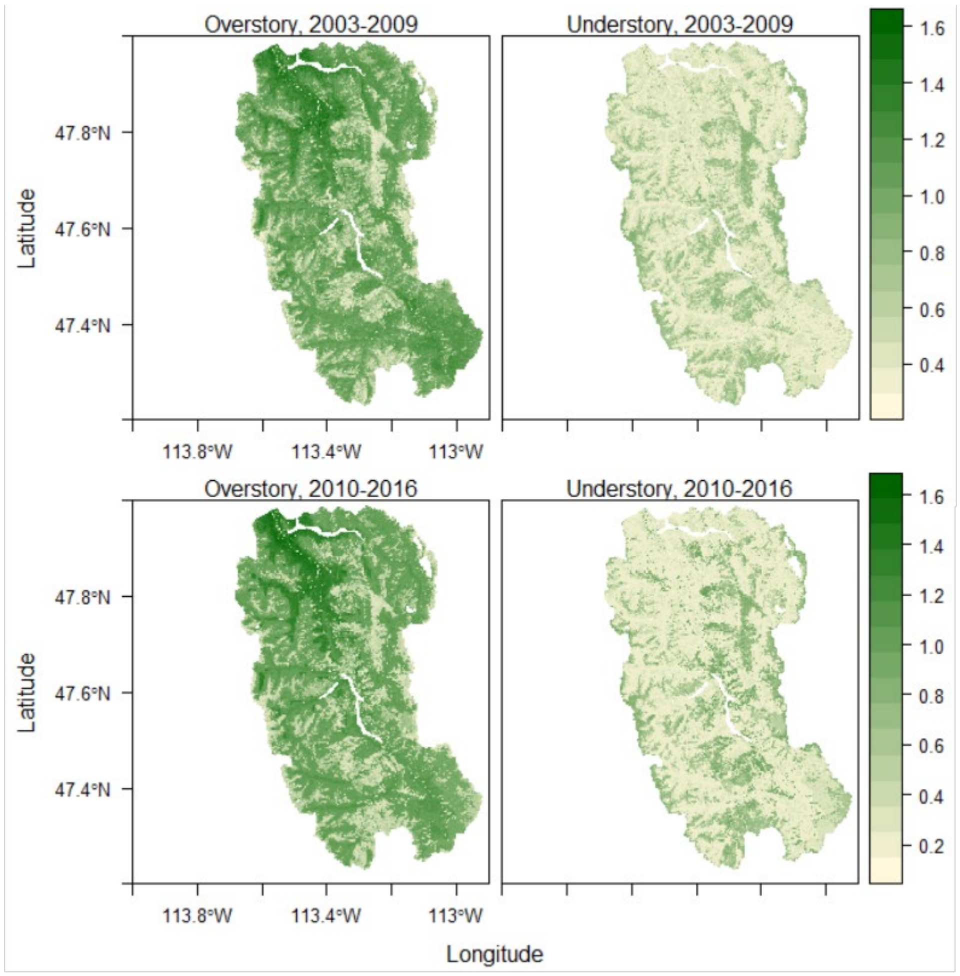

Figure 2. Overstory and understory leaf area index in the South Fork Flathead watershed, Montana, for two time periods: 2003-2009 and 2010-2016

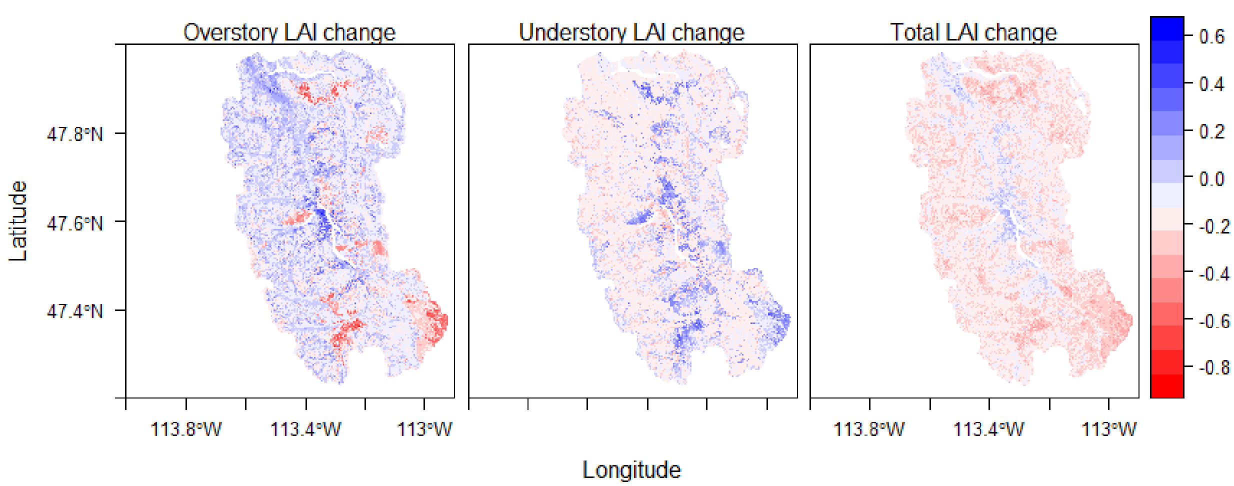

Figure 3. Change in overstory, understory, and total LAI between two time periods (2003-2009 and 2010-2016)

References

Andréassian, V. 2004. "Waters and forests: from historical controversy to scientific debate," Journal of Hydrology, 291:1-27.

Biederman, J. Somor, A.J., Harpold, A.A., Gutmann, E.D., Breshears, D.D., Troch, P.A., Gochis, D.J., Scott, R.L., Meddens, A.J. and Brooks, P.D. 2015. "Recent tree die-off has little effect on streamflow in contrast to expected increases from historical studies," Water Resources Research, 51(12):9775-9789.

Bosch, J. and Hewlett, J. 1982. "A review of catchment experiments to determine the effect of vegetation changes on water yield and evapotranspiration," Journal of Hydrology, 55:3-23.

Breiman, L. 2001. "Random forests," Machine Learning, 45(1):5-32.

Burrill, E.A.; Wilson, A.M.; Turner, J.A.; Pugh, S.A.; Menlove, J.; Christiansen, G.; Conkling, B.L.; David, W. 2017. The Forest Inventory and Analysis Database: Database description and user guide version 7.2 for Phase 2. U.S. Dept. of Agriculture, Forest Service. 946 p. [Online]. Available at web address: http://www.fia.fs.fed.us/library/database-documentation/. Last accessed 23 April 2019.

Daly, C., Taylor, G.H., Gibson, W.P., Parzybok, T.W., Johnson, G.L., and Pasteris, P.P. 2001. "High-quality spatial climate data sets for the United States and beyond," Transactions of the American Society of Agricultural Engineers, 43: 1957-1962.

Eidenshink J., Schwind B., Brewer K., Zhu Z., Quayle B., and Howard S. 2007. "A project for monitoring trends in burn severity," Fire Ecology, 3(1):3–21.

Ellis, C., Pomeroy, J., Essery, R. and Link, T. 2011. "Effects of needleleaf forest cover on radiation and snowmelt dynamics in the Canadian Rocky Mountains," Canadian Journal of Forest Research, 41(3):608-620.

Harpold, A.A., Biederman, J.A., Condon, K., Merino, M., Korgaonkar, Y., Nan, T., Sloat, L.L., Ross, M. and Brooks, P.D. "Changes in snow accumulation and ablation following the Las Conchas Forest Fire, New Mexico, USA," Ecohydrology, 7(2):440-452.

Homer, C.G., Dewitz, J.A., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N.D., Wickham, J.D., and Megown, K. 2015. "Completion of the 2011 National Land Cover Database for the conterminous United States-Representing a decade of land cover change information," PERS, 81: 345-354.

Liaw, A., and M. Wiener. 2002. "Classification and regression by randomForest," R News, 2(3):18–22.

Lundquist, J., Dickerson-Lange, S., Lutz, J. and Cristea, N. 2013. "Lower forest density enhances snow retention in regions with warmer winters: A global framework developed from plot-scale observations and modeling," Water Resources Research, 49(10):6356-6370.

McCune, B. and Keon, D. 2002. "Equations for potential annual direct incident radiation and heat load," Journal of Vegetation Science, 13:603-606.

R Core Team. 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Available online: http://www.R-project.org/[Accessed 15 February 2019].

Robinson, N.P., Allred, B.W., Jones, M.O., Moreno, A., Kimball, J.S., Naugle, D.E., Erickson, T.A., and Richardson, A.D. 2017. "A dynamic Landsat derived normalized difference vegetation index (NDVI) product for the conterminous United States," Remote Sensing, 9(8): 863.

Slinski, K., Hogue, T., Porter, A. and McCray, J. 2016. "Recent bark beetle outbreaks have little impact on streamflow in the Western United States," Environmental Research Letters, 11(7):074010.

Tague, C. and Band, L. 2004. "RHESSys: Regional Hydro-Ecologic Simulation System—An object-oriented approach to spatially distributed modeling of carbon, water, and nutrient cycling," Earth Interactions, 8:1-42.

Tesfa, T.K., Tarboton, D.G., Watson, D.W., Schreuders, K.A.T., Baker, M.E., and Wallace, R.M. 2011. "Extraction of hydrological proximity measures from DEMs using parallel processing," Environmental Modelling & Software, 26: 1696-1709.

Troendle, C. 1983. "The potential for water yield augmentation from forest management in the Rocky Mountain region," Journal of the American Water Resources Association, 19:359-373.

U.S. Department of Agriculture, Forest Service. 2013. Interior West Forest Inventory and Analysis Forest Survey field procedures, Ver. 5.0. Available online: http://www.fs.fed.us/rm/ogden/data-collection/pdf/iwfia_p2_60.pdf [Accessed 18 December 2018].

Wigmosta, M., Vail, L. and Lettenmaier, D. 1994. "A distributed hydrology-vegetation model for complex terrain," Water Resources Research, 30:1665-1679.

Xiao Z., Liang, S., Wang, J. Wang, Chen, P., Yin, X., Zhang, L., and Song, J. 2014 "Use of general regression neural networks for generating the GLASS leaf area index product from time series MODIS surface reflectance," IEEE Transactions on Geoscience and Remote Sensing, 52(1):209-223.