Method

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Sentinel 2

Compared to Landsat multispectral bands, the Sentinel-2 multispectral bands provide two red edge bands and one NIR band with improved spatial resolution. The Sentinel 2 bands can be used to derive various vegetation indices useful for discriminating between species and estimating forest biomass (Tab. 1)

Table. 1: Overview Sentinel 2 bands (Arcgis.com)

Band	Description	Wavelength..um.	Resolution..m.
1	Coastal Aerosol	0.433 - 0.453	60
2	Blue	0.458 - 0.523	10
3	Green	0.543 - 0.578	10
4	Red	0.650 - 0.680	10
5	RE1	0.698 - 0.713	20
6	RE2	0.733 - 0.748	20
7	RE3	0.773 - 0.793	20
8	NIR	0.785 - 0.900	10
8a	Narrow NIR	0.855 - 0.875	20
9	Water vapour	0.935 - 0.955	60
10	SWIR-Cirrus	1.365 - 1.385	60
11	SWIR-1	1.565 - 1.655	20
12	SWIR-2	2.100 - 2.280	20

Vegetation Indices

Vegetation indices including near-infrared wavelength have weaker relationships with biomass than those including shortwave infrared wavelength, especially for forest sites with complex stand structures. The results of image transformations such as the first principal component from the PCA showed stronger relationships with biomass than individual spectral bands, somehow independent of different biophysical conditions. However, in a study area with poor soil conditions and relatively simple forest stand structure, near-infrared band or relevant vegetation indices had a strong relationship with biomass (Lu et al., 2016)

Table. 2: Vegetation Indices derived from Sentinel 2 information (after Pandit et al., 2018)

Vegetation.Indices	Equations	References
NDVI	(NIR - R/NIR + R)	(Tucker 1979)
RGR (Red Green Ratio)	Red665/Green560	(Sims & Gamon 2002)

Vegetation.Indices	Equations	References
EVI (Enhanced Vegetation Index)	2.5*((NIR - R)/ (1 + NIR + 6R - 7.5 Blue))	(A. Huete et al. 2002)
SR (Simple ratio)	NIR/RED	(Jordan 1969)
PSRI (Plant Senescence Reflectance Index)(665 - 560/740)	(Hill 2013; Merzlyak et al. 1999)	
NDII (Normalized Difference Infrared Index)	(842 - 1610/842 + 1610)	(Hardisky et al. 1983)
RE NDVI	842 - 740/842 + 740	(Chen et al. 2007)
SAVI (Soil-Adjusted Vegetation Index)	(NIR - R)/(NIR + R + L)*1.5	(Huete 1988)
RECI (Inverted Red-Edge Chlorophyll Index)	NIR - R/(RE1/RE2)	(Frampton et al. 2013)
Sentinel-2-red-edge position	[705 + 35*(0.5*(B7 + B4)/2) - B5)/(B6 - B5)]	(Frampton et al. 2013)
Red-edge-based NVDI's		
1	(NIR - RE1/NIR + RE1)	(Kross et al. 2015)
2	(NIR - RE2/NIR + RE2)	(Gitelson & Merzlyak 1994; Kross et al. 2015)
3	(NIR - RE3/NIR + RE3)	(Sharma et al. 2015)
4	(NIR - RE4/NIR + RE4)	(Kross et al. 2015)

Estimation of forest AGB using Sentinel-2-derived information was based on the extension of a tree-based model called Random Forest (Breiman, 2001). In this algorithm, decision trees are generated to the maximum extent without pruning using a randomly-selected two thirds of the samples as training data with bootstrapping (re-sampling the data many times with replacement), which strengthens the flexibility by aggregating the prediction across individual trees to make a final prediction (Pandit et al., 2018). The paper ranks importance of spectral band data and vegetation indices from above (Tab. 1) as a typical output of a random forest.

Normalised Burn Ratio

The Normalized Burn Ratio (NBR) is an index designed to highlight burnt areas in large fire zones. The formula is similar to NDVI, except that the formula combines the use of both near infrared (NIR) and shortwave infrared (SWIR) wavelengths.

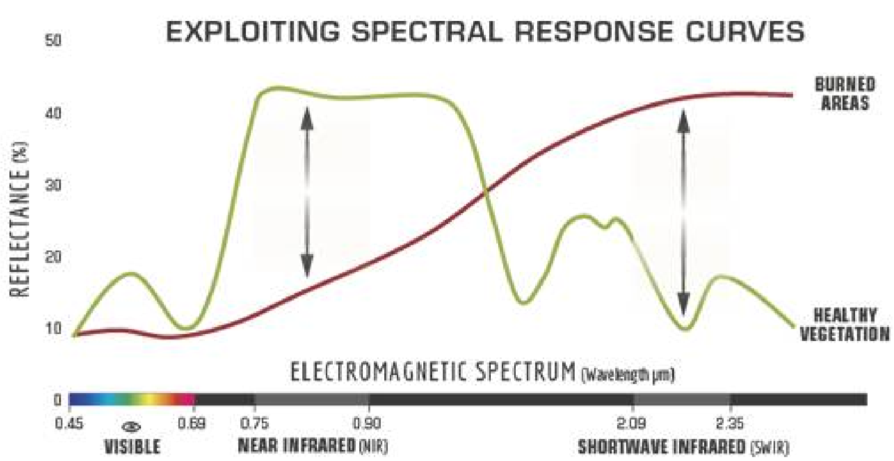

Fig: 1 Comparison of the spectral response of healthy vegetation and burned areas (USFS)

LiDAR

LiDAR for biomass quantification.

Recent paper with Jonathan and Van Kane (Hudak et al. 2020). Used a Carbon Monitoring System (CMS) to produce annual estimates of aboveground biomass using machine-learning algorithms Random Forests (RF). Field plots collected by the US Forest Service (USFS) and other stakeholders in 29 areas in northwestern USA. Plot level AGB estimates were used as a response variable to predict AGB from LiDAR derived canopy height and density information (R2 = 0.8, RMSE = 115 Mg ha-1, Bias = 2 Mg ha-1).

'A stratified random sample of AGB pixels from these landscape-level AGB maps then served as training data for predicting AGB regionally from Landsat image time series variables processed through LandTrendr'
climate metrics calculated from downscaled 30 year climate normals were used as predictors for both models (landscape and regional), as were topographic metrics calculated from elevation data; these environmental predictors allowed AGB estimation over the full range of observations with the regional model (R2 = 0.8, RMSE = 152 Mg ha-1, Bias = 9 Mg ha-1), including higher AGB values (>400 Mg ha-1) where spectral predictors alone saturate.

Found both our project landscape and regional, annual AGB estimates to be unbiased with respect to FIA estimates (Biases of 1% and 0.7%, respectively)

combination of LiDAR and other imagery for biomass estimation

Long-standing research question in lidar remote sensing for AGB estimation is to understand whether the addition of passive optical imagery to airborne lidar can further improve AGB modeling performance (Dengsheng Lu et al., 2016).

Combination of lidar and QuickBird image did not improve AGB estimation in mixed coniferous forests in California; lidar data alone provided a better performance (Hyde et al., 2006)

LiDAR and hyperspectral combination has lower accuracy than LiDAR alone in tropical forest Costa Rica (Clark et al., 2011).

As a result research has shifted to use non-parametric algorithms such as KNN, artificial neural network, support vector regression (SVR) and random forest (RF).

Field data

Shana sampling plots

Sampling plot data from the Forest Inventory and Analysis National Program (FIA). Sampling plots are available

- Allometric: DBH, size classes (e.g. saplings) > height groups, largest tree measured, height to live crown, crown ratio, crown width, age data sparse and based on 1-2 cores
- Biomass derived from LiDAR datasets
- plot center GPS using Javad
- plot date and size
- Ancillary data: Slope, ground cover, vegetation cover by type (e.g. shrub, forb, etc), modal vegetation height by different types of vegetation, fuel models, fuels data, seedlings, site history (e.g. plantation, if there was a fire, etc)

Sampling echniques used: https://www.fia.fs.fed.us/program-features/index.php

Biomass estimation in the field

Collection of a large number of biomass reference data at the plot level is time-consuming and labor-intensive. It is only suitable for a small area and cannot provide the spatial distribution. However, this kind of data is a prerequisite for developing biomass estimation models (Lu et al., 2016). Allometric models most common, but require data about soil, land use history and climate influence (paper here for tropical) (Clark & Kellner, 2012).

(table lu et al 2016)

Use data of national forest inventories:

ABG (kg/ha) = volume (m3 / ha) * VEF * WD * BEF +

with volume expansion factor (VEF), average wood density (WD), biomass expansion factor (BEF) (Brown et al., 1989; Lehtonen et al., 2004; Wang et al., 2011)

Problems with field data

(1) tree variables, including sampling, measurement, recording and grouping errors when tree variables such as DBH and height are measured;
(2) conversion coefficients and models including variation of conversion factors from volume to biomass and then to carbon, inappropriate selection and usage of allometric models for relationship of tree volume and DBH and height, and incorrect regression models relating forest biomass/carbon to spectral variables;
(3) uncertainties of spectral values due to unbalanced platforms, scanner motions, poor atmospheric conditions, and slope; inappropriate spatial interpolation methods for geometrical and radiometric corrections, and incorrect methods for image enhancement and analysis;
(4) sample plot locations, including global positing system (GPS) coordinates used to locate the sample plots, geometric correction and the uncertainties due to mismatch of sample plots with spatial resolutions of remotely sensed data;
(5) differences in sizes of sample plots and image pixels, disagreement between remotely sensed data and plot observations when portions of trees on boundaries are outside plots although both sample plots and pixels have the same spatial resolutions; and
(6) temporal differences between field plot measurements and remotely sensed data.

Landsat

Jonathan Kane paper (Kolden et al., 2012). We characterized unburned area within fire perimeters by fire size and severity, characterized distance to an unburned area across the burned portion of the fire, and investigated patch dynamics of unburned patches within the fire perimeter. From 1984 through 2009, the total area within the fire perimeters that was classified as unburned from dNBR was 37% for Yosemite, 17% for Glacier, and 14% for Yukon-Charley.

Synthetic aperture radar (SAR)

Most radar-based biomass estimation studies use L-band SAR data, especially the ALOS PALSAR L-band data (Mitchard et al. 2011; Carreiras et al. 2012; Rahman and Sumantyo 2013). The SAR C-band data have not been extensively used because of the C-band's inability to capture forest biomass features (Le Toan et al. 1992; Lu 2006).

In summary, it is difficult to use radar data for distinguishing vegetation types (Li et al. 2012b) because radar data reflect the roughness of land cover surfaces instead of the difference between the vegetation types, thus resulting in difficulty of biomass estimation. The speckle in radar data is another problem affecting its applications. Properly employing filtering methods to reduce noise and outliers in InSAR data is needed to improve the vegetation height estimation performance (Kellndorfer et al. 2004).

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