Combined airborne LiDAR and spectral satellite data for three-dimensional fuels mapping in sagebrush-steppe

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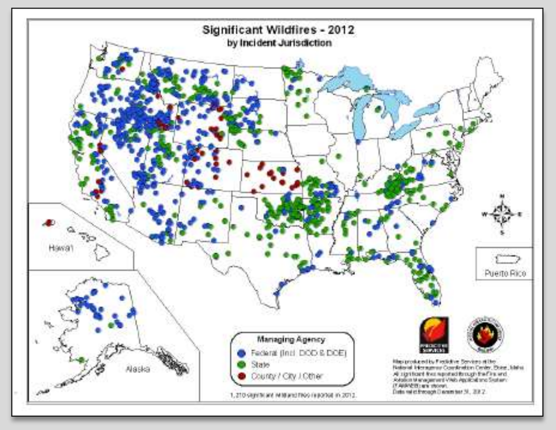
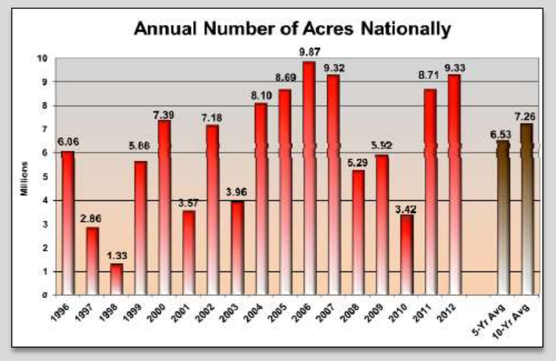
Introduction

In the past 15 years, the western U.S. has experienced record fire activity, in terms of size, frequency, and intensity. Fire in the Great Basin sagebrush-steppe ecosystem has resulted in cheatgrass invasion across millions of acres. The “invasive plant-fire regime cycle” alters nutrient and hydrologic cycles and when coupled with additional disturbance factors such as drought and overgrazing, the ecosystems can trends toward desertification, threatening food and water security. Accurate spatially explicit fuel maps are essential inputs for fire prediction modeling and post-fire treatment across spatial and temporal scales. While laser altimetry (airborne or ground-based) can provide detailed 3D fuel metric information related to vegetation structure, coverage is expensive and limited both spatially and temporally. Multispectral satellite observations provide repeat and large scale coverage but under-contribute to 3D vegetation structure mapping across the landscape.

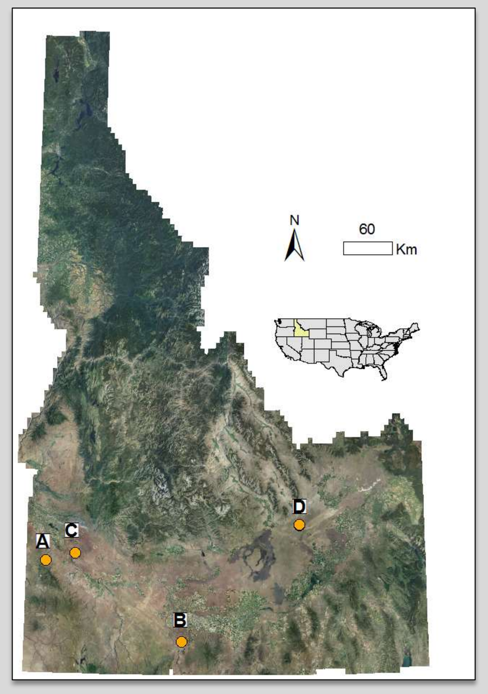




Source: http://www.nifc.gov/fireInfo/fireInfo_statistics.html

Study Sites

This study focuses on predicted HyspIRI capabilities over Hollister and RCEW collection sites in southern Idaho. We also draw upon related preliminary results from ongoing investigations at sites near the Snake River Birds of Prey National Conservation Area (BoP) and within the 2010 Jefferson Fire boundary.



A. Reynolds Creek Experimental Watershed
- 270 km^2
- LiDAR (2007)
- Hyperspectral (2010)

B. Hollister
- 20 km^2
- LiDAR (2011)
- Hyperspectral (2010)

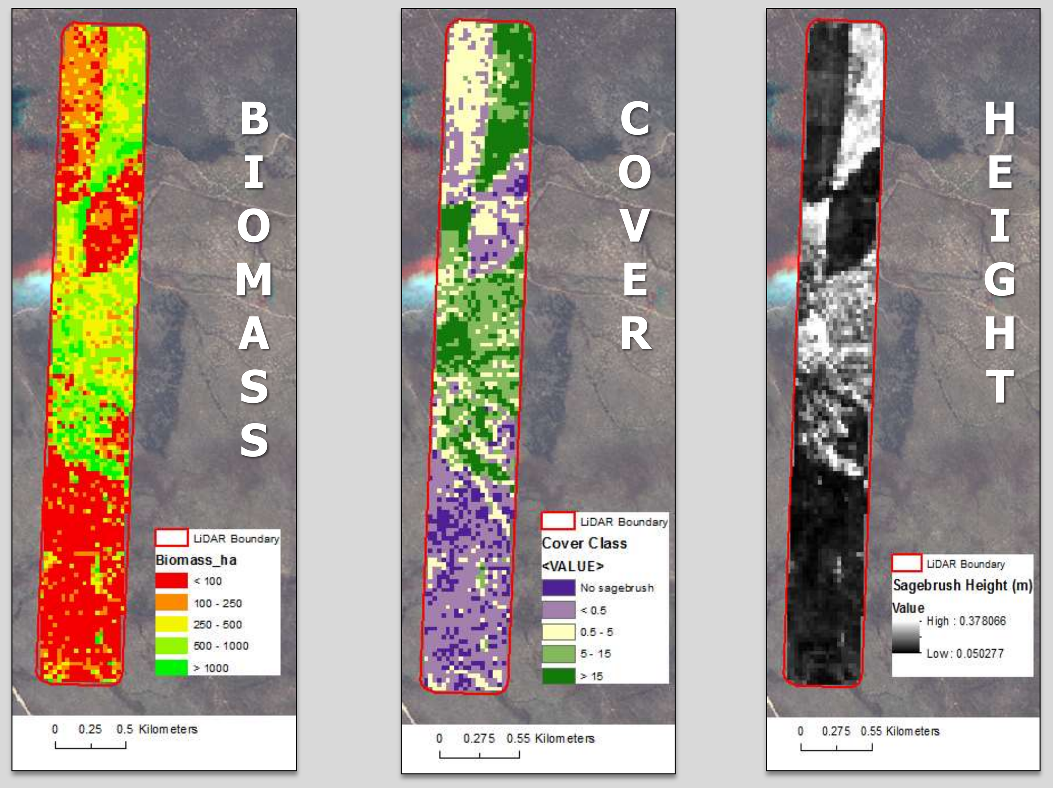
C. Birds of Prey
- 2.87 km^2
- LiDAR (2011)

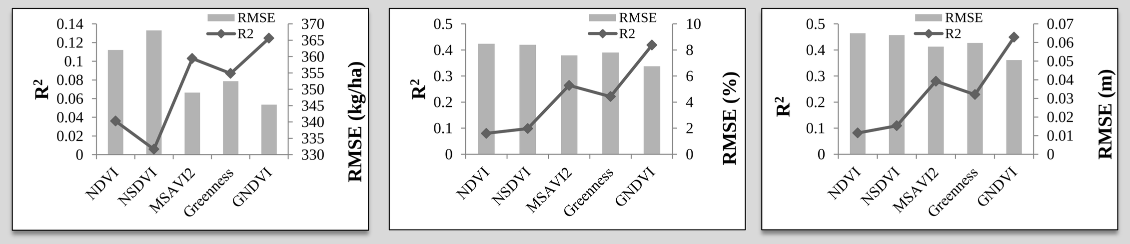
D. Jefferson Fire
- 400 km^2

Discrete return LiDAR data were collected using a Leica ALS50II data and hyperspectral imagery were acquired in early August using a HyMap sensor with a 2 to 3 m pixel resolution.

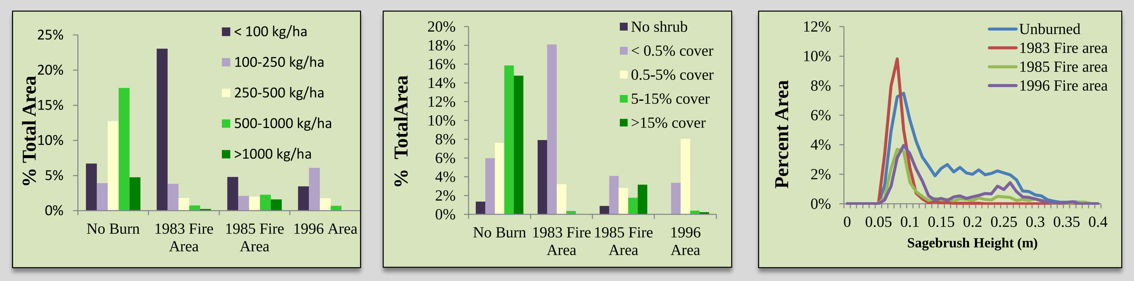
LiDAR Shrub Metrics vs. Landsat VIs

At BoP, distributions of LiDAR-derived shrub biomass, cover, and height estimates were evaluated across unburned areas and areas. The LiDAR-derived metrics were also related to Landsat Indices to consider the feasibility of tracking changes in fuel loading across large spatial extents using satellite observations.



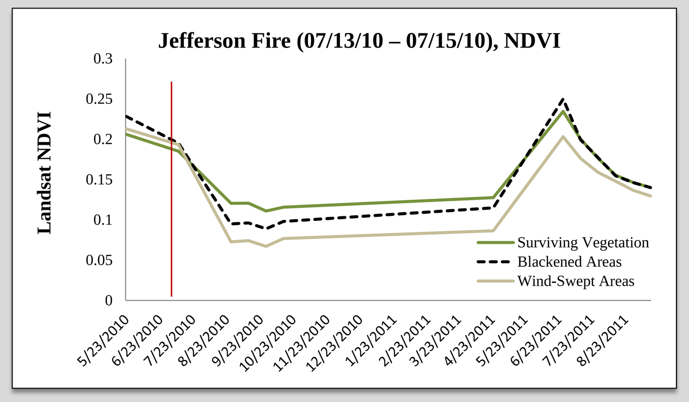


Relationship between Landsat 5 vegetation indices (date: 09/13/2011) and LiDAR vegetation biomass (n = 3007)



A comparison of biomass, cover and height across burned and unburned areas suggests that shrubs are not recovering in areas burned during the 1983 fire

Jefferson Fire and Landsat NDVI Time-Series



Although a Landsat NDVI time-series does not quantify fuel metrics, it can provide insight into post-fire processes. Here, NDVI values one year after fire indicates wind affected areas are not recovering.

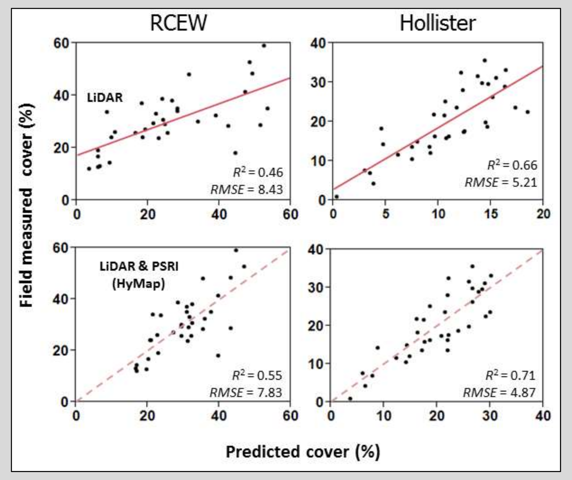
On the ground, one year after the Jefferson fire, cheatgrass invasion is occurring (center photo, background)

HyspIRI Simulation

- LiDAR and hyperspectral imagery (HyMap) obtained over the Hollister and RCEW sites were used to simulate the extent to which HyspIRI satellite observations could improve estimates of cover and height in sparsely vegetated environments.
- Pre-processing: 1) cross track illumination corrections were applied to mosaicked HyMap flightlines, 2) LiDAR point cloud data were height filtered and converted to 2 m raster products using BCAL LiDAR Processing Tools. Raster products included maximum vegetation height, vegetation cover (number of returns > 15 cm / total number of returns) and intensity, 3) HyMap and LiDAR datasets were co-registered to within 1 pixel using a combination of HyMap true and false color displays and LiDAR intensity layers.
- Cover estimation was validated by establishing cover plots on the ground concurrent with HyMap acquisitions (n = 20 for each site). For each plot, point intercept and transect sampling was used to estimate percent cover for live and dead shrub species, grasses, forbs, litter, rock and bare ground). Ground sampling estimates were regressed against cover estimates derived from LiDAR and LiDAR +HyMap datasets (Mitchell et al., in prep).
- Shrub vegetation height was validated in a series of previous studies for the RCEW site and a site in southeastern Idaho (Glenn et al., 2011; Mitchell et al, 2011).
- To simulate HyspIRI observations, HyMap imagery (472.0 – 2486.7 nm; ~ 13.4 – 20.6 nm FWHM) were spectrally resampled to match AVIRIS channels (472.4773 – 2477.1960n m; ~ 9.2 -11.9 nm FWHM), then spatially coarsened from a pixel resolution of 2.1 m to 60 m.
- A total of 446 pixels (60 m) were randomly selected from the simulated HyspIRI imagery: RCEW, n = 277; Hollister, n = 169). For each pixel, reflectance bands, the first 10 MNF transformed bands, and a series of vegetation indices were related to vegetation height and cover estimates directly computed from the filtered point cloud data. Indices considered included (NDVI, SRI, EVI, ARVI, VREI, REPI, NDLI, PSRI, WBI, MSI, NDII).
- Random Forests variable selection was used to select the best spectral predictors of height and cover for use in nearest neighbor imputations models (Breiman, 2001, Crookston and Finley, 2008; Hudak et al., 2008).

Results: Random Forests Imputation with LiDAR, Hyperspectral and HyspIRI

Cover estimates derived from LiDAR and from LiDAR combined with Plant Senescence Reflectance Index (PSRI; (680 nm – 500 nm)/ 750 nm) compared to cover plots estimated on the ground using a point intercept method.



Random Forests Variable Selection

Variable Importance from Random Forests regression (both RCEW and Hollister sites)

Vegetation height is best explained by VSWIR bands 511nm and 2357nm, and normalized difference infrared index (NDII). Vegetation cover is best explained by Red Edge Position Index (REPI), Vogelmann Red Edge Index (VREI),Water Band Index (WBI), and VSWIR bands 694nm and 1998 nm.

MEAN VEGETATION HEIGHT

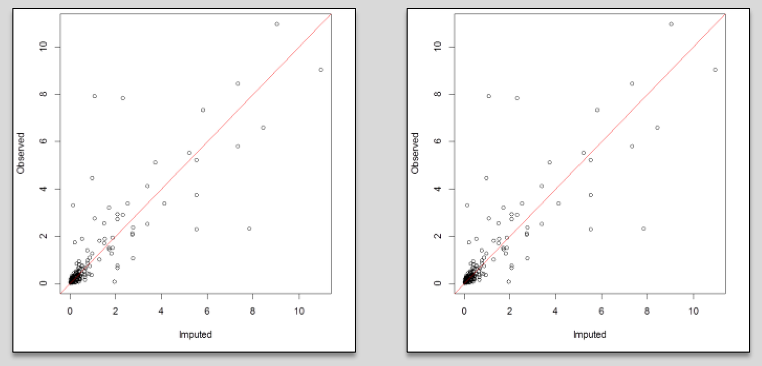
HyspIRI - simulated Variables (Gini Score in parenthesis)	R2	RMSE
Band_2357.967041 (100)	0.64	0.76
Band_2357.967041 (100), NDII (57)	0.69	0.70
Band_2357.967041 (100), NDII (55), Band_511.353485 (36)	0.71	0.69
NDII (100), Band_2357.967041 (97), Band_511.353485 (83), MNF_5 (53) ★	0.74	0.65

VEGETATION COVER

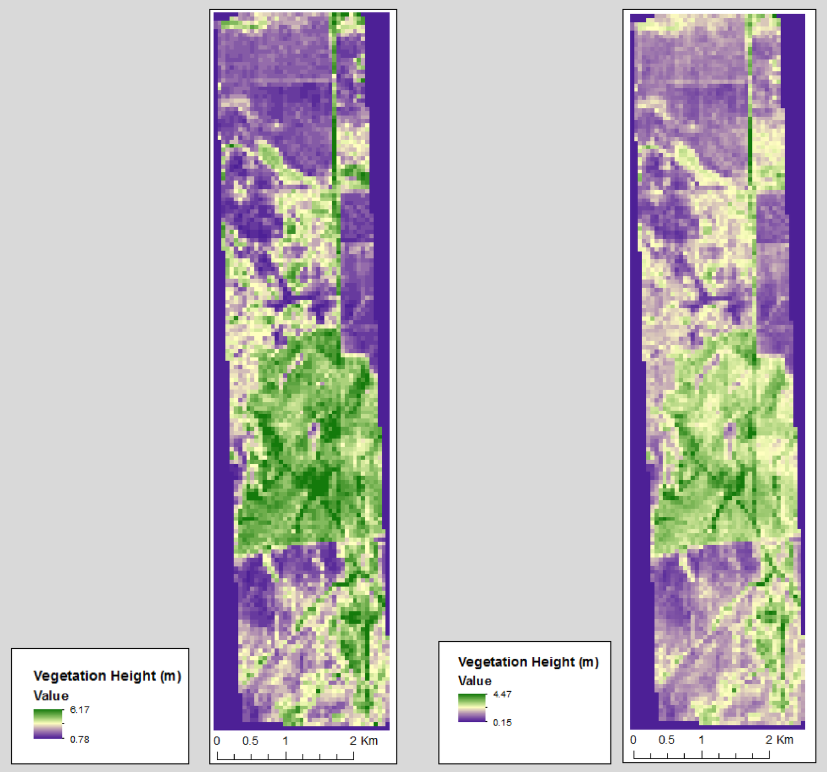
HyspIRI - simulated Variables (Gini Score in parenthesis)	R2	RMSE
REPI (100)	0.63	11.79
REPI (100), VREI (76.41)	0.58	12.45
REPI (100), VREI (46.47), WBI (35.52)	0.68	10.95
REPI (100), VREI (68.96), WBI (58.96), Band_694.48938 (58.27)	0.71	10.33
REPI (100), VREI (69.0), WBI (44.4), Band_694.48938 (43.1), Band_1998.284058 (41.4) ★	0.72	10.19

★ Variables selected to run nearest-neighbor imputation

Nearest Neighbor Imputations



Vegetation structure (height and cover) estimates from the imputation model using simulated HyspIRI variables were significantly correlated with LiDAR–derived measures of the vegetation structure (r^2>0.72, p=0.001).



Comparison of vegetation heights derived directly from rasterized LiDAR (left) and from Nearest Neighbor Imputation Model using simulated HyspIRI variable (right).

Conclusions

- Any future cover studies should consider PV vs NPV and shrub vs grass as well as the LiDAR metric: height interquartile range, which has been shown to perform well as a LiDAR predictor or shrub cover (Mitchell et al., in prep).
- Shrub mapping improvements need to leverage the full range of hyperspectral information (Ustin et al., 2009) and in combination with LiDAR and tools such ISU BCAL’s LiDAR height filtering algorithms, which have been developed for open canopy landscapes.
- Vegetation height prediction results warrant further investigation into potential for HyspIRI to augment vertical structure measurements in dryland systems where future LiDAR satellite technologies may be sensitive to areas of low canopy cover.

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