Mapping Horizontal and Vertical Distribution of Fuel by Fusing High-Resolution Hyperspectral and Polarimetric Data

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Final Report

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Robert Crabtree[1]

Kerry Halligan[1]

Sassan Saatchi[2]

Richard Aspinall[3]

Don Despain[4]

[1] Yellowstone Ecosystem Research Center, Bozeman, MT. [2] Jet Propulsion Laboratory, Santa Barber, CA. [3] School of Geographical Sciences, Arizona State University, Tempe, AZ. [4] Northern Rocky Mountain Science Center, Bozeman MT.

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Introduction

The current fire situation with numerous very large fires that regularly cross agency boundaries has shown a major need for improved fuels maps. Small fires require only simple maps that can be hand drawn on large scale base maps during a reconnaissance flight but large fires and major planning projects require accurate maps covering thousands of acres that provide relevant fuels data at a local scale. **C**urrent small scale fuel maps are largely agency specific making it necessary for fire managers and planners to be familiar with more than one system. These systems often differ in resolution of both classification units and map unit size creating confusion and frustration in interagency projects. There is need for common maps that cover very large areas. Remote Sensing in the form of radar and optical images fused into a single entity has the potential to provide such maps. There is a critical need for cost-effective remote sensing methodologies that render accurate, efficient fuel maps for landscape to regional scales.

This project explored the possibility of combining these two types of remotely sensed data. It was divided into two parts: *a*. extracting fuel parameters using a combination of remote sensing types including radar and optical images and *b*. the presentation of the results in a form readily useful to fire managers through GIS processes

Summary

We developed a variety of remote sensing and GIS methods and products that map wildland fuels according to specific vegetation types (fuel models) and the horizontal and vertical position of biomass, two factors significantly affect the intensity and spread of fires. We collected airborne hyperspectral and LiDAR, satellite-based ASTER (multispectral), airborne polarimetric and interferometric SAR, and forest fuel ground validation (n=833 plots in 64 stands) in four primary areas within YNP that are representative of vegetation types in the GYE. Unique algorithms and classification procedures applied to the hyperspectral data were used to map NFFL fuel types as well as fuel condition, defined as the fraction of live vegetation to senescent vegetation. SAR data were used to accurately estimate canopy, bole, and total biomass of structured vegetation types (shrubs to moderate biomass level forests). It was also used to subdivide NFFL fuel types into biomass levels. A major goal of this research was to assess the added value of combining multiple datasets in the analysis of fuel distribution. This assessment was conducted using two separate levels (approaches). The first was to include both optical and SAR data in the model building phase of the research and the second was to combine optimal results from each dataset to produce an enhanced final dataset. Data fusion was not found to be helpful for estimation of crown biomass or the fuel components that can be derived from crown biomass values. Overall, for level 1, where raw data were used, SAR data outperformed optical data. For level 2, optical data products performed slightly better than SAR data products. Surprisingly, when fusion levels 1 and 2 were

compared, raw SAR data outperformed the SAR data products. Optimal fusion results were achieved when optical data products were combined with raw SAR data in a Level 1/2 hybrid. We also provided recommendations based on lessons learned during this research to guide fire analysts, researchers and fire managers with a roadmap for further investigations and applications (sensor costs, accuracies and other characteristics). Finally, in our opinion a multi-tiered approach is needed to adequately map and monitor fuels across YNP and the GYA. This multi-tiered approach must account for spatial variability that is a result of environmental conditions, land use and disturbance history. It must also account for the temporal variability in fuels that occurs throughout the fire season as well as on larger time scales.

We then generated a GIS model that provides a framework describing relationships between image-derived fuel properties of different elements of forests, including tree, shrub, herbaceous, and downed wood layers, as well as tree crown and boles. The data model also allows these elements to be aggregated or otherwise combined to represent forest stands. Stands can be defined by forest planting and harvesting plans, by analysis of the spatial variability of the forest characteristics as measured by remote sensing, or from other definitions. Once defined, the attributes for stands potentially include a very wide variety of values including total, maximum, mean, variance for biomass in each of the tree, shrub, herbaceous, and downed wood components that comprise the stand. A GIS can compute these values for each stand from the pixel level description of forests once stands are defined.

Remote Sensing Analysis and Classification

Deliverables

Optical Image Acquisition and Processing

1) Archival ASTER data were assessed, downloaded, radiometrically and atmospherically processed and georeferenced.
2) An ASTER data processing guide was developed that includes custom IDL software for processing ASTER data
3) HyMap data collection campaign was developed, planned, and initiated with field data collection conducted concurrent to data collection
4) HyMap data were atmospherically and geometrically corrected
5) SRTM elevation data were acquired for entire GYE and were processed to calculate slope, aspect and elevation and convert data into project coordinate system (UTM,

zone 12, NAD83). An SRTM data processing guide was developed that includes custom IDL software for processing SRTM data.

SAR image Acquisition and Processing

1) Archival SIR-C data were requested, acquired and processed to backscatter (dB)
2) AIRSAR data collection campaign was developed, planned, and initiated with field data collection conducted concurrent to data collection
3) AIRSAR data were terrain corrected and processed to backscatter (dB)
4) SAR data sets (including processed and terrain corrected AIRSAR, SIR-C) delivered? to the study team, including geo-referenced high-resolution AIRSAR data.

Field Data Acquisition and Processing

1) Field data collection efforts were planned for supporting classification efforts and biomass retrieval efforts across a broad swath of YNP and a range of vegetation types and disturbance histories. These methods were tested and implemented during 2 seasons of field data collection including field crews of 6 people for 3 months each.
2) Existing allometric equations and biomass equations were investigated for suitability for YNP fuels and biomass calculations. A database was developed using MS Access and VBA to calculate field data to biomass.
3) Field data were processed using database and provided along with differentially corrected GPS data of all field sites to all investigators
4) Field data were collected to support AIRSAR data collection. Measurements included soil moisture data collected across a range of soil moisture levels, and additional forest height measurements. All field data in support of SAR work was provided to study team.
5) Field data were assessed for validation and training for retrieval of vegetation biomass parameters at the all study sites.

Optical Analysis Methodology

1) Methodologies were evaluated for suitability for vegetation/fuels type classification. Decision trees were determined to be an optimal approach due to non-parametric nature, interpretability and high classification accuracies.
2) IDL routines that facilitate Classification Tree classification were developed using the Splus and R software package and the ENVI/IDL analysis environment. Routines allow for the creation of single and multiple decision trees and the classification of images from trees. Options include cross-validation, ensemble approaches, fuzzy classifications and generation of uncertainty maps.
3) IDL routines were developed to implement Spectral Mixture Analysis (SMA) and Multiple Endmember Spectral Mixture Analysis (MESMA) using images and spectral libraries in the ENVI environment. This work has lead to the development of a fully

functional end-user software suite that is an ENVI add-on called VIPER Tools which is freely available at http://www.geog.ucsb.edu/~halligan/viper/viper_tools.html.

4) IDL software was developed for classification of digital color photography to retrieve % cover of green vegetation for estimating herbaceous fuel load with minimal destructive harvesting
5) ENVI interface for a wide range of new IDL-based image processing software was developed that includes routines for:
    a. Implementation calculating both multispectral and hyperspectral vegetation indices (NDVI, SAVI, NDWI, PRI, EWT, etc.)
    b. An extensive toolbox for dealing with field data including shapefiles and Regions of Intrest (ROIs) and for extracting image data for field sites

Optical Mapping Products

1) Classification tree map products were produced for ASTER and HyMap datasets and presented in the 2003 annual report as well as at the presentation at the April 2004 JFSP PI workshop in Phoenix and the YNP YCR presentation in May 2004. These products were also supplied to all collaborators for evaluation and feedback. Revisions were made in Feb 2005 and May 2005 to improve results.
2) SMA data products were produced for ASTER and HyMap datasets and presented in the 2003 annual report as well as at the presentation at the April 2004 JFSP PI workshop in Phoenix and the YNP YCR presentation in May 2004. These products were also shown to all collaborators for evaluation and feedback. Revisions were made in Feb 2005, May 2005, and May 2006 to improve results.
3) Maximum likelihood classifications of Landsat and HyMap data using a new training dataset developed using aerial photo interpretation, LiDAR data, and existing fuel maps and used to classify the HyMap and Landsat data with a Maximum Likelihood (ML) approach. The ML maps provided appear to represent a higher quality fuel model data product based on a qualitative comparison to the imagery and existing fuel maps.

SAR Mapping Products

1) Biomass of forests (foliage, branch, bole) and non-forests (grasslands and shrublands) from SIR-C data
2) Biomass classes   Binned biomass classes from SIR-C data
3) Biomass of forests (foliage, branch, bole) and non-forests (grasslands and shrublands) from high-resolution AIRSAR data
4) Biomass classes, binned biomass classes from high-resolution AIRSAR data

Fusion Mapping Products

1) Fusion images of hyperspectral data with SAR data were created to show as a single visualization both the total biomass and fuel type classification. These data were provided to collaborators in May 2005 and were presented to the GYA FMO's at their

biannual meeting in Bozeman, MT. Final versions of these maps were created in May of 2006 and represent fusion results for both HyMap and Landsat ETM+ NFFL fuel model classifications with AIRSAR crown biomass. These maps are provided as final Fusion Level 3 deliverables.

2) Fusion Level 1 and 2 analysis of HyMap and AIRSAR data was conducted to assess tradeoffs between fusion approaches as well as data inputs. Figures and tables showing methods and accuracies are provided as final deliverables along with maps which were developed from optimal fusion.

Publications and Conference Proceedings

1) Saatchi, S., Despain, D., Halligan, K. and Crabtree R. (2006) Estimation of Forest Fuel Load from Radar Remote Sensing. IEEE Trans. on Geoscience and Remote Sensing. Accepted.

2) Dennison, P.E., **K.Q. Halligan** and D.A. Roberts, 2004. A comparison of error metrics and constraints for multiple endmember spectral mixture analysis and spectral angle mapper. *Remote Sensing of Environment*, 93, 359-367

3) Peterson, S., Goldstein, N., Clark, M., **Halligan, K.**, Schneider, P., Dennison, P. and Roberts, D. (2005). Sensitivity Analysis of the 2003 Simi Wildfire Event. Proceedings of the 8th International Conference on GeoComputation, August 1-3, 2005, University of Michigan, Eastern Michigan University, USA.

4) In preparation:

   a) Classification of wildland fuels in Yellowstone with Decision Tree Analysis
   b) Mapping wildland fuel condition in Yellowstone using Spectral Mixture Analysis
   c) Use of inteferometry data for forest height estimation using SRTM and AIRSAR data.

Education and Outreach:

1) Presentation at GYA FMO meeting in West Yellowstone, June 2003 and in Bozeman, May 2005 to present research project
2) Presentation at JFSP PI workshop in Phoenix, AZ April 2004
3) Presentation at YNP YCR May 2004
4) Training workshop at YERC May 2004 and Feb 2005 to present optical image analysis and IDL programming
5) Development and updating of YERC JFSP website to communicate project objects and methods. See www.geog.ucsb.edu/~halligan/yfp/index.htm

Major Research Findings

Given the large quantity of datasets, data types and analysis approaches used in this research we attempt here to provide a useful summary of our findings as a companion to the final data products. Under each category below we discuss the data and analysis methods used, challenges faced and successes achieved. Where appropriate, deliverables that resulted from the method being described are called out. Following this section, a recommendations section builds off the lessons learned during this research to provide researchers and fire managers with a roadmap for further investigations.

Remote Sensing Data Types

Two major data types were assessed in this work: passive optical data (hyperspectral and multispectral data) and active microwave (Synthetic Aperture RADAR - SAR) data. Generally, passive sensors are successful in classification of "2-D surface" cover and vegetation types. Relying upon illumination of features with photons from sunlight (hence passive), optical sensors don't penetrate surface features such as vegetation and thus cannot provide estimates of 3-D structure. However, active sensors like SAR and LiDAR can. Consistent with the wealth of scientific literature, SAR data were used to conduct the bulk of the fuel load retrieval while optical data were utilized mainly for 2-D classification purposes.

As a windfall to this project YERC was able to leverage other ongoing research projects to obtain high resolution LIDAR data during the 2003 field campaign over study sites in the Northeast corner of the Park. Analysis of these data are included here to a limited extent in the hopes of providing some comparisons to the optical and SAR datasets in order to aid the reader in assessing the utility of this increasingly used data type.

SAR (Synthetic Aperture Radar)

SAR data are sensitive to vegetation architecture, soil moisture and above ground biomass and have been shown in the literature to be a suitable dataset for estimating biomass in temperate ecosystems. Data from SIR-C (1994) and AIRSAR (2003) were used in this research to accurately retrieve above ground biomass, (crown, bole, and total) in this study.

It should be noted that SAR data are a fairly complicated remote sensing dataset with relatively high cost to analysis and produce final mapping products. The modeling routines developed during this research needed to account for complex physical properties within canopies and the effects of local incidence angles (LIAs). This can be difficult to achieve and an advanced level of training is needed. Another disadvantage is the high cost of airborne SAR sensors. For example, NASA's cost to cover an area the size of YNP is estimated at ~50K. The few commercially available airborne SARs would cost more.

One of the major promising results of our work was the ability of SAR sensors to accurately extract canopy, bole, and total biomass of structured vegetation types (shrubs to moderate biomass level forests). This combined with the recent and future planned launches of satellite-based SARs will allow fire managers a viable method of estimating 3-D structure and fire fuel parameters important to predicting the behavior of crown-dominated fire systems. In addition, satellite SAR data are relatively low cost and provide wide area coverage that are more stable than airborne platforms. This will reduce the cost of processing and analysis of SAR (one of its disadvantages), for example, by reducing the costs associated with removing the effects of LIA.

Another major advantage of SAR is its ability to work in daytime, nighttime, clouds and no-clouds. The price of satellite platforms are relatively moderate to high but new European and Asian systems will be lower in cost (e.g., ~ $10K to cover YNP). These new satellite systems are promising in that they are polarimetric (HH, VV, and HV) and have increased spatial resolution (1 to 10 meters). Fully polarimetric C- and L-band systems are currently in operation. A high resolution L-band system (3-meter) is planned for launch in 2008 as well as the planning and construction of a satellite P-band system.

Satellite interferometric SAR systems like NASA's short-term SRTM (shuttle radar topography mission) is also being planned for launch (Tandem-X). Two antenna interferometric SAR provides an important alternative for estimation of vegetation height and vegetation profiles to that of LiDAR.

Multispectral

Multispectral data are the most commonly used type of remote sensing data and have been shown to be a reliable data source for broad classification of surface types. In this research multispectral data from ASTER (2001-2003) and Landsat ETM+ (1999) were used to map NFFL fuels models in the study area. Advantages of satellite platform multispectral data like ASTER and ETM+ is their affordability (< $1K to cover YNP) and ease of analysis. Their disadvantages include their unreliability due to cloud cover, inability to measure 3-D vegetation structure (biomass and height), and their relatively low classification accuracies even for generalized cover types (60% to 80% accuracies are common).

The original proposal called for the use of ASTER data as the primary multispectral data set. These data were collected and extensively processed and analyzed for mapping NFFL fuel models. Code was developed for processing these data to reflectance which incorporates radiometric calibration, atmospheric correction, geometric correction and correction of systematic errors including the 'cross-talk' phenomenon. Despite the effort invested in this dataset, several problems were encountered which limited the utility of this dataset. ASTER is a tasked pointable sensor and it was not tasked under this research. Instead, we relied on archive data collected by other investigators. This resulted in sub-optimal locations and timing of the data acquisitions which prevented the creation of a consistent mosaic with suitable solar geometry and vegetation phenology. For example, the viewing geometry in some scenes created large Bidirectional Reflectance Distribution Function (BRDF) effects which caused considerable differences in NFFL fuel model classifications from one scene to another. Sub-optimal solar geometry also enhanced the negative effects cause by topography compounding classification errors.

To address these shortcomings the best currently available Landsat ETM+ scene (9/15/1999) was used to provide a single consistent dataset over the study sites. This dataset was classified for NFFL fuel models and was used in Fusion Level 3 to produce integrated fuel type and load visualizations. Because topographic effects persisted in the Landsat data and appeared to contribute confusion between NFFL fuel models 8 and 10 based on local solar incidence angle differences attention was placed on this common problem. A new software module that applies an empirical model of reflectance based on the cosine of the local incidence angle was created and integrated into the beta version of the VIPER Tools ENVI Add-in being developed by Co-PI Kerry Halligan in cooperation with UCSB. This software solution is primarily focused on Spectral Mixture Analysis (SMA) which was used extensively in this research to address fuel condition mapping. The software is freely available and can be downloaded at http://www.geog.ucsb.edu/~halligan/viper/viper_tools.html. While this terrain correction algorithm is now complete and available to users, the timing of its creation did not allow for a re-processing of optical datasets to remove the influence of topography. We feel that this step would improve the results of this study we intend to incorporate this approach into future research.

Hyperspectral

Airborne hyperspectral data are much more complicated to process and analyze than multispectral data due to their large data volume and more complex viewing geometry. While studies have shown increased performance of hyperspectral data over multispectral data with regards to classification accuracy, the real strength of hyperspectral data is their ability to capture physical properties by measuring the location and strength of particular absorption features. Most notably, hyperspectral data have been used to map mineral types, amount liquid water, vegetation stress and sub-pixel abundance of surface types. Compared to multispectral, hyperspectral data provides a much wider and diverse set of biophysical parameters that can be estimated. In addition, it achieves significantly higher classification accuracies that multispectral. However, another disadvantages is it’s high cost. Currently, the only hyperspectral sensor (with relatively low cost) on a satellite platform is Hyperion on the EO-1 satellite. Due to it’s experimental nature and low reliability (cloud cover) and low coverage (7 km swath), it’s practical application for mapping fire fuels is low.

In this research airborne HyMap data (2003) was successfully used to map NFFL fuel types as well as fuel condition, defined as the fraction of live vegetation to senescent vegetation. Hyperspectral has a bright future for mapping fuels as well as it’s ability to discriminate significantly more cover and vegetation types – even species ID -- than compared to multispectral.

LiDAR (LIght Detection And Ranging)

While not included in this proposal we also conducted some preliminary tests on the ability of small-footprint LiDAR for fuel estimation. LiDAR data are well suited for mapping vegetation structure and have been widely used in the literature for forestry and fuel mapping applications. Major limitations to these data are that their high-resolution (~1m or finer) result in very large data volumes and very high data costs ($20 to $30K per USGS 7.5 minute quad). Additionally, there is very limited software on the market for analyzing these data and all efforts in this work were conducted with custom software applications. Currently, there is a large footprint, non-scanning LiDAR on a satellite platform but it provides little capability of extracting vegetation structure and has very limited areal coverage.

While LiDAR data represent the highest possible accuracy they are largely impractical for mapping of large scale patterns in fuel distribution due to costs of data collection and data analysis. They do provide an excellent data source for subsets of a study area however and are being increasingly used as a validation data source. Our work with LiDAR over the Northeast corner of the Park indicates that the horizontal and vertical accuracy of small footprint LiDAR make them a suitable validation data sets (for SAR, for example) if a limited field dataset is available for calibration of height offsets.

Data Temporal Frequency

Selection of an optimal remote sensing data set often represents a tradeoff between temporal scale and spatial resolution. The datasets evaluated here were mostly single collection datasets – that is, systems that must be tasked to collect data rather than repeat pass systems such as orbital non-tasking satellite systems. This was true for the SIR-C, AIRSAR, HyMap, ASTER and LIDAR datasets. The only exception to this was the Landsat ETM+ data which includes a sun-synchronous 16-day repeat cycle. This combined with the large (185km x 185km) image extent would make ETM+ a good candidate for baseline mapping of fuels. Unfortunately, the Scan Line Corrector, which compensates for the forward motion of the satellite during data acquisition, failed on May 31, 2003 causing large physical gaps near the edge of each picture. One high frequency sensor which was not evaluated in this research but which may prove useful to the fire community is MODIS. With daily data collections the MODIS sensor provides timely information on vegetation health and can be used to estimate fuel moisture as well as fuel condition. The largest limitation is the spatial resolution of these data which range from 250 m to 1 km depending on the band and data product desired. Integrating the timely MODIS data products with higher resolution baseline maps from higher resolution systems might provide the best approach to mapping and monitoring wildland fuels in the GYA.

Data Spatial Scale

The spatial scale and pattern produced by remote sensing data products more closely matches observed fuels distributions than typical aerial photo interpretation efforts due to the 1 to 1 match between pixel values and biomass value or fuel model type. This is both a benefit and a liability to the end user. It is a benefit in that the data are not spatially averaged which may reduce or remove local areas of high or low fuel loads. It is a liability in that it presents a large amount of information which needs to be interpreted, especially where fuels are heterogeneous across the landscape. Smoothing of data products can help produce generalized results to aid interpretation of results.

Fire modeling efforts often use spatial scales ranging from 30m to 1km, depending on the source of their input data sets. In this research spatial scales ranged from 10m to 30m depending on datasets. AIRSAR and HyMap data were analyzed on a common 10m spatial scale, while Landsat and SIR-C data were processed at ~30m (28.5m-30m).

There is very limited research on the effect of spatial scale on fire management decision support systems. As a part of this research one modeling effort focused on spatial scale and heterogeneity was conducted on fuels in Southern California (Peterson et al. 2005). In that research different fuel data layers were used to model a single wildland fire and results were compared to mapped fire fronts derived from MODIS active fire data products. In general it was found that heterogeneity of fuels greatly affected the spread rates in the FARSITE model. This might suggest that remote sensing derived data layers, which are in general much more heterogeneous that other fuel maps may produce unexpected results in the FARSITE model which has largely been calibrated to historical fuel maps. Further research is needed to assess the effects of using remote sensing derived fuel maps as inputs to existing fire decision support systems.

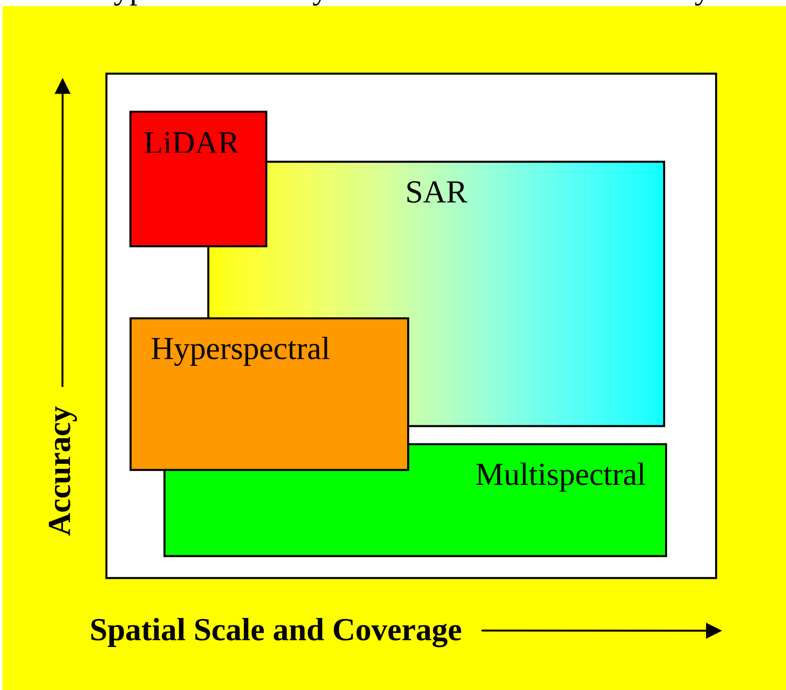
Data Spatial Extent

One challenge with large scale ecological processes such as wildland fire is that datasets used to map, monitor and model this phenomena must be both large in spatial extent and consistent across the study area. Remote sensing data hold the promise of providing consistent datasets over large scales and are thus a promising data type for fire management. This research, however, has shown the challenges that result from finer scale datasets such as the higher resolution HyMap and ASTER datasets where limited swath widths require multiple flightlines which can result in expensive data collects, large processing costs and potentially a range of acquisition times and dates that create challenges with local solar geometry and incidence angle. Where suitable, large scale data products such as space borne datasets such as PALSAR (L-band SAR system on ALOS) and MODIS provide potential solutions to the large spatial extent needed for mapping large areas such as the GYA.

Optimal Data Set Decisions

Consistent with the original project deliverables, we herein provide a decision matrix table or “road map” to enable end-users cost vs. utility in assessing remotely sensed approaches to fire fuels. A general road map is provided below that depicts the relative range of accuracy vs. spatial scale. A more specific decision matrix is provided in the table below and includes a wider range of characteristics. The specific characteristics listed in the column headings of this qualitative table are discussed in the above sections for each type of RS data included.

Generalized Schematic of the relative tradeoff between accuracy and spatial scale for various types of remotely sensed data used in our analysis.



A qualitative matrix to aid in decisions to use RS data types.

SENSOR	Cost to acquire	Data reliability	Resolution (m)	Accuracy (% or r2)	Analysis costs	Species ID ?	Cover type ?	Biomass ?	Stand height ?
SAR (satellite)	moderate	high	1 to 30	0.50 to 0.90	high	mod./low	mod./high	mod./high	moderate
SAR (airborne)	high	mod./high	1 to 10	0.60 to 0.95	high	mod./low	mod./high	mod./high	moderate
Multispectral (satellite)	low/variable	low	3 to 30	50 to 90	moderate	low	moderate	low	low
Hyperspectral (airborne)	mod./high	moderate	1 to 20	70 to 95	mod./high	mod./high	high	moderate	low
LiDAR (airborne)	high	moderate	1 to 3	0.80 to 0.98	moderate	low	high	high	high

Training and Validation Data

With the focus of this work on estimating the vertical distribution of fuels a statistically rigorous sampling design was developed and implemented. This approach utilized unsupervised classification, image segmentation and a regular sampling grid to generate as unbiased of a field data set that could be achieved given the available resources. Data collection at these field sites resulted in 833 samples from 64 stands within a linear transect from Old Faithful (WY) to Cooke City (MT). The field data can be found in an archive file which includes spreadsheets, GIS data and web pages and images for all sites.

While the extensive field dataset was ideal for the goal of mapping the vertical structure of fuels from active remote sensing data (RADAR and LIDAR) the randomness utilized in its creation limited it utility as a training or validation dataset for fuel model mapping. This is because while the field data adequately covered the range of fuel loads in the study area, they did not always represent conditions typical of particular fuel classes.

Anomalies present biased the statistics of the modeling algorithms and created poorer than expected fuel model classifications. Fuel model classifications were improved when a highly representative but biased training dataset was developed using aerial photo interpretation, LIDAR data analysis, and existing fuel maps. See the maximum likelihood classifications using Landsat ETM+ and HyMap data for these improved classifications.

These findings suggest the need for two types of training and validation datasets – one for mapping continuous variables which covers the range of possible conditions and one for mapping classes which captures variability within classes but represents typical conditions of each surface type.

Analysis Methodologies (Single Datasets)

SAR

Based on previous research by research team member Sassan Saatchi, an improved approach was developed which incorporated field data with SAR backscatter models to produce a semi-empirical modeling approach. This method was used to retrieve biomass values for tree boles and vegetation canopies which were further segmented into foliage, 1 hour and 10 hour fuels as well as estimates of crown bulk density. Details on the methods and results from the SAR modeling can be found in the manuscript by Saatchi which has been accepted for publication.

In addition to the semi-empirical approach a simple linear and non-linear regression modeling effort was undertaken as a comparison to previous studies and to results that could be obtained from optical datasets. It was found that the advanced methodology of the semi-empirical approach far out-performed simple linear and non-linear regression efforts by leveraging the known physical relationship between vegetation components and particular polarizations in the SAR data. The semi-empirical approach was able to remove much of the non-linear effects seen as SAR backscatter saturates with higher biomass levels.

Optical

Linear and non-linear regression modeling was conducted to model crown biomass using optical data bands and optical data products. Consistent with the literature, these efforts showed saturation at higher biomass values at greater rates than the SAR data, resulting in a non-linear that prevented inference at higher biomass level. Best results from this effort can be seen in the data fusion figures in the PDF files provided.

For classification purposes two main approaches were utilized. The first was the standard maximum likelihood estimation approach where classes are modeled as multivariate normal distributions parameterized with their band means, variances and covariances. The maximum likelihood approach assumes normal distributions as well as similar data scales for all input data layers. In theory this precludes the use of highly non-Gaussian date sets such as SAR data where data also differ greatly from optical data due to their log scale. To account for this, analysis of the SAR data and fused (Data Fusion Levels 1 and 2) was conducted using classification and decision tree (CART) analysis. More details on CART are provided below.

Analysis Methodologies (Data Fusion)

A major goal of this research was to assess the added value of combining multiple datasets in the analysis of fuel distribution. This assessment was conducted using two separate approaches. The first was to include both optical and SAR data in the model building phase of the research and the second was to combine optimal results from each dataset to produce an enhanced final dataset. These two approaches can be categorized into 3 different Fusion Levels:

Fusion Level 1 (Spectral Level Fusion)

Fusion Level 1 involves model building (classification and/or regression analysis) on raw image bands. For SAR data this includes the dB data while for optical data this includes apparent surface reflectance. Data from multiple sensors are combined into a co-registered data stack and used to drive models. The model creation optimizes locally to select the most suitable data inputs at any particular step in the model. In this research the Random Forest algorithm was implemented in R for building classification and decision tree ensembles. Models were evaluated on withheld data using cross validation to assess model accuracy.

Fusion Level 2 (Decision Level Fusion)

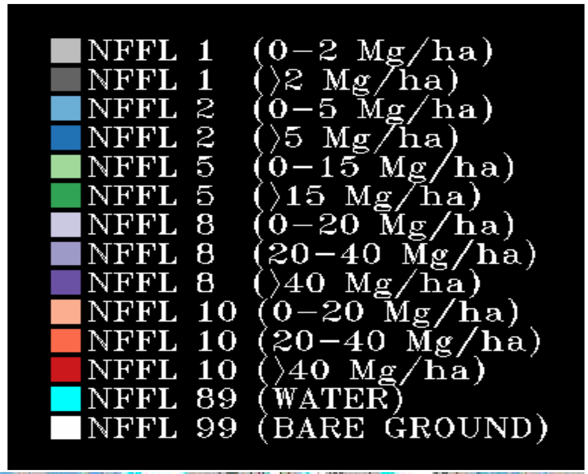
Similar to above, Fusion Level 2 combined bands from SAR and optical data into Random Forest CART analysis. In Fusion Level 2, however, SAR and optical data products, rather than the raw data themselves, where used to drive the modeling process. For SAR data products, crown and bole biomass estimation data layers produced by the semi-empirical modeling effort were used as model inputs. For optical data, a large number of vegetation indices and spectral metrics which measure the strength of spectral absorption features were used as inputs. CART analysis then proceeded to select among these data products to build ensemble models for predicting fuel loads and fuel model classes.

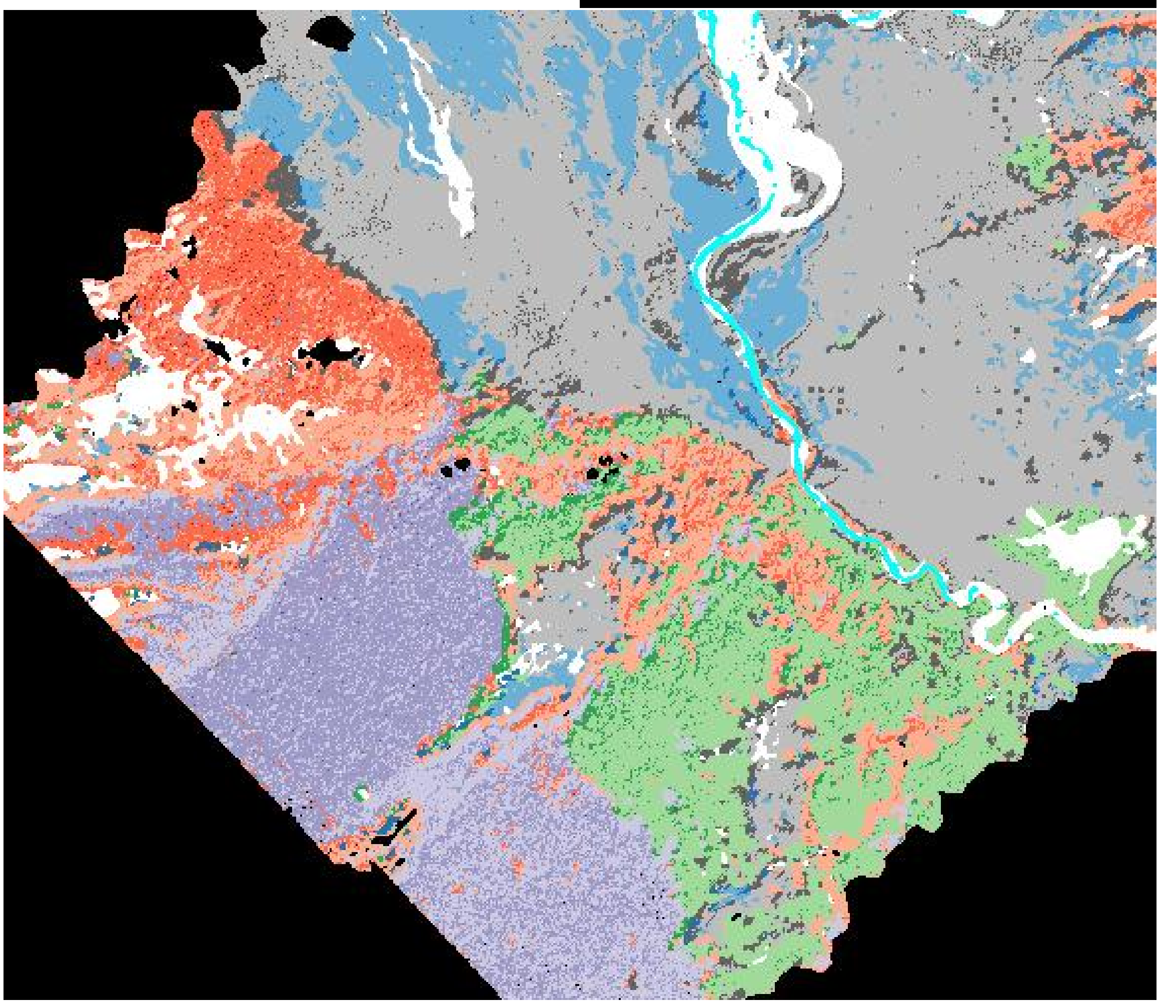
Fusion Level 3 (Visualization Level Fusion)

Fusion Level 3 represents a combination of 2 or more data products into a single multidimensional visualization. This was undertaken in this research in an attempt to provide a single representation that combines the two main data products of this research: crown biomass (canopy fuel) and NFFL fuel model.

Classifications are generally displayed with unique colors for each class, while continuous variables such biomass values are generally displayed with a gradient of one or more colors from light to dark. To create Level 3 fusion products for this research we selected a basic color scheme for each class then developed gradients within each color to capture a limited number of ranges of crown biomass values. Color Brewer (www.colorbrewer.org) was used in this research in an attempt to maximize visual separation of classes and gradients. The image below shows the map key developed using Color Brewer RGB values.

Level 3 fusion products were created using the AIRSAR bole biomass data created by Sassan Saatchi fused with both Landsat (1999 scene) and HyMap data as classified with Maximum Likelihood Estimation (described above). The image below shows an example of this fused visualization over an area with a range of fuel conditions along the Lamar River near Opal Creek.





Summary of Fusion Results

Fusion levels 1 and 2 for estimation of crown biomass produced accuracies that were below those of the SAR data products produced through the semi-empirical modeling approach. In addition the fusion results showed the non-linear effects in the final models, whereas the semi-empirical approach accounted for these non-linear effects in the modeling process. Thus data fusion was not found to be helpful for estimation of crown biomass or the fuel components that can be derived from crown biomass values. This is likely because the optical data saturate at lower biomass ranges and thus when they are used add confusion and saturation effects into the model results.

Fusion results for levels 1 and 2 for classification of NFFL fuel models are outlined in the table below. For level 1, where raw data were used, SAR data outperformed optical data. For level 2, optical data products performed slightly better than SAR data products. Surprisingly, when fusion levels 1 and 2 were compared, raw SAR data outperformed the SAR data products. Optimal fusion results were achieved when optical data products were combined with raw SAR data in a Level 1/2 hybrid.

Table 3. Classification results for all individual and combined datasets showing overall accuracy, kappa coefficient, and the minimum user's and producer's accuracy for CART classifications. For all model runs all 44 stands were used in a leave-one-out cross-validation. Subscripts ref, feat, bs and bio indicate reflectance, spectral features, backscatter and derived biomass, respectively.**

Input Dataset(s)	Overall Accuracy	Kappa	Minimum User's Accuracy (class)	Minimum Producer's Accuracy (class)
$HyMap_{ref}$	63.3%	0.499	14.8% (10)	21.3% (10)
$HyMap_{feat}$	71.9%	0.614	23.6% (10)	36.1% (10)
$AIRSAR_{bs}$	75.7%	0.665	44.0% (10)	60.6% (10)
$AIRSAR_{bio}$	70.0%	.596	34% (10)	53.6% (10)
$HyMap_{ref}$ + $AIRSAR_{bs}$	70.3%	0.588	26.3% (10)	39.3% (10)
$HyMap_{feat}$ + $AIRSAR_{bs}$	80.9%	0.733	43.2% (10)	51.3% (5)
$HyMap_{ref}$ + $AIRSAR_{bio}$	61.9%	0.484	5.5% (10)	9.8% (10)
$HyMap_{feat}$ + $AIRSAR_{bio}$	77.6%	0.688	28.8% (10)	37.7% (10)

** Note that these results show the optimal data fusion results of this study based on statistically rigorous accuracy assessment. This provides an assessment of the tradeoffs that can be achieved with the various data inputs and provides validation of the Random Forest CART algorithm for mapping NFFL fuel models with fused datasets. This approach did not, however, produce the best maps from an overall spatial pattern (see ML classification description above).

Qualitative assessment of the optimal fused map data products suggest showed systematic errors such as misclassification of fuel model 5 as fuel model 8. Upon close inspection of the field data, it was determined that outliers in the fuel model 5 training data which included one or more live canopy trees were driving the statistics and producing sub-optimal classifications. Outliers in other classes could be seen to be contributing to errors in other classes. To address this, a second training dataset was selected using aerial photo interpretation, LiDAR data, and existing fuel maps and used to classify the HyMap and Landsat data with a Maximum Likelihood (ML) approach. The ML maps provided appear to represent a higher quality fuel model data product based on a qualitative comparison with the imagery and existing fuel maps.

Recommendations

Ecosystem-wide Remote Sensing Derived Base map:

A base map should be developed using SAR data from a satellite platform. Basing this mapping on SAR data will take advantage of this superior data type for single data mapping of fuel loads and fuel models. Use of a satellite platform will improve viewing geometry, reduce error (especially roll correction that can plague airborne platforms like AirSAR) and provide a cost effective system that will allow for repeat data collections. Currently, the recently launched ALOS PALSAR sensor is the most suitable for this application. Several other satellite launches of polarimetric SAR sensors are planned over the next few years including high resolution X-, C-, L-, and P-band.

Since there is already an ecosystem-wide fuels map (GYA fuels map based on the Cumulative Effects Model data) priority should focus on areas where fuels are not well mapped or where significant disturbances have changed the distribution of fuels. In addition, remote sensing offers a standardized method of updating changing fuels over time. Other priorities should include areas of higher risk to human life including the wildland urban interface where more detailed data would help decision makers.

Field Data:

High quality reference data are critical for both model building and validation using remote sensing. Special considerations concerning spatial resolution and accuracy are required for field data to be suitable for integration into remote sensing data analysis. As remote sensing is increasingly used on a large scale in the GYA to address fire management issues, an updated field data set will become an increasingly important resource. If these measurements are made in a consistent manner from large homogeneous areas they can provide a physical link between image derived data and actual field measured foliar moisture.

GIS Data Modeling

GIS data modeling is a mechanism for formal description of relationships between elements of a spatial database. In this case data modeling provides a formal description of relationships between forests and fuel from the inter-related data elements and attributes accessible from remote sensing. The data model needs to a) describe relationships between the different elements of forests, b) set the fuel properties of forests within the context of environmental variability in landscapes as described using GIS datasets for topography and other characteristics, c) provide a mechanism for linking fuel data with existing and future fire models, and d) link the pixel-based representation of remote sensing with stand and polygon representations of forests.

GIS Data Management

A geographic information system (ESRI ArcGIS) is used to manage all data layers and integrate final products using data modeling techniques. A project GIS database was developed from the National Spatial Data Infrastructure Clearinghouse managed and maintained by the Geographic Information and Analysis Center (GIAC) at Montana State University. These environmental data describe the study area's underlying topography and other resources. The forest fuel data model links to this topographic and environmental database through a wide variety of data management and processing tools provided by the GIS. The database serves as an environment within which to integrate vegetation type, fuel, and biomass maps to create linkages with fire models. For example, fuel spatial connectivity cannot be measured directly with remote sensing but can be created from the topology (geographical connectedness) of fuel parameters within the GIS. Using data modeling to link the outputs from sensor fusion analyses with the geographic data management and analysis capabilities of GIS allows spatial characteristics of fuel to be described and measured. These linkages can then be integrated with other properties for incorporation into fire models that require GIS layers as inputs. Developing these linkages is a significant contribution of the project, providing a mechanism for rapid deployment of remotely sensed parameters into an analytical applications environment.

A Data Model for Forest Fuel

The data model developed for fuel attributes measured from remotely sensed data by YERC is shown in Figure 1. This model provides a framework that describes relationships between image-derived fuel properties of different elements of forests, including tree, shrub, herbaceous, and downed wood layers, as well as tree crown and boles. These are all elements that potentially can be measured using remote sensing, either at a pixel level or, with very high spatial resolution imagery relative to the size of the features in the landscape, at an individual tree level. This suite of data model elements provides a structure that allows fully spatially disaggregated data, as available from remote sensing systems, to be stored.

The data model also allows these elements to be aggregated or otherwise combined to represent forest stands. Stands can be defined by forest planting and harvesting plans, by analysis of the spatial variability of the forest characteristics as measured by remote sensing, or from other definitions. Once defined, the attributes for stands potentially include a very wide variety of values including total, maximum, mean, variance for biomass in each of the tree, shrub, herbaceous, and downed wood components that comprise the stand. A GIS can compute these values for each stand from the pixel level description of forests once stands are defined.

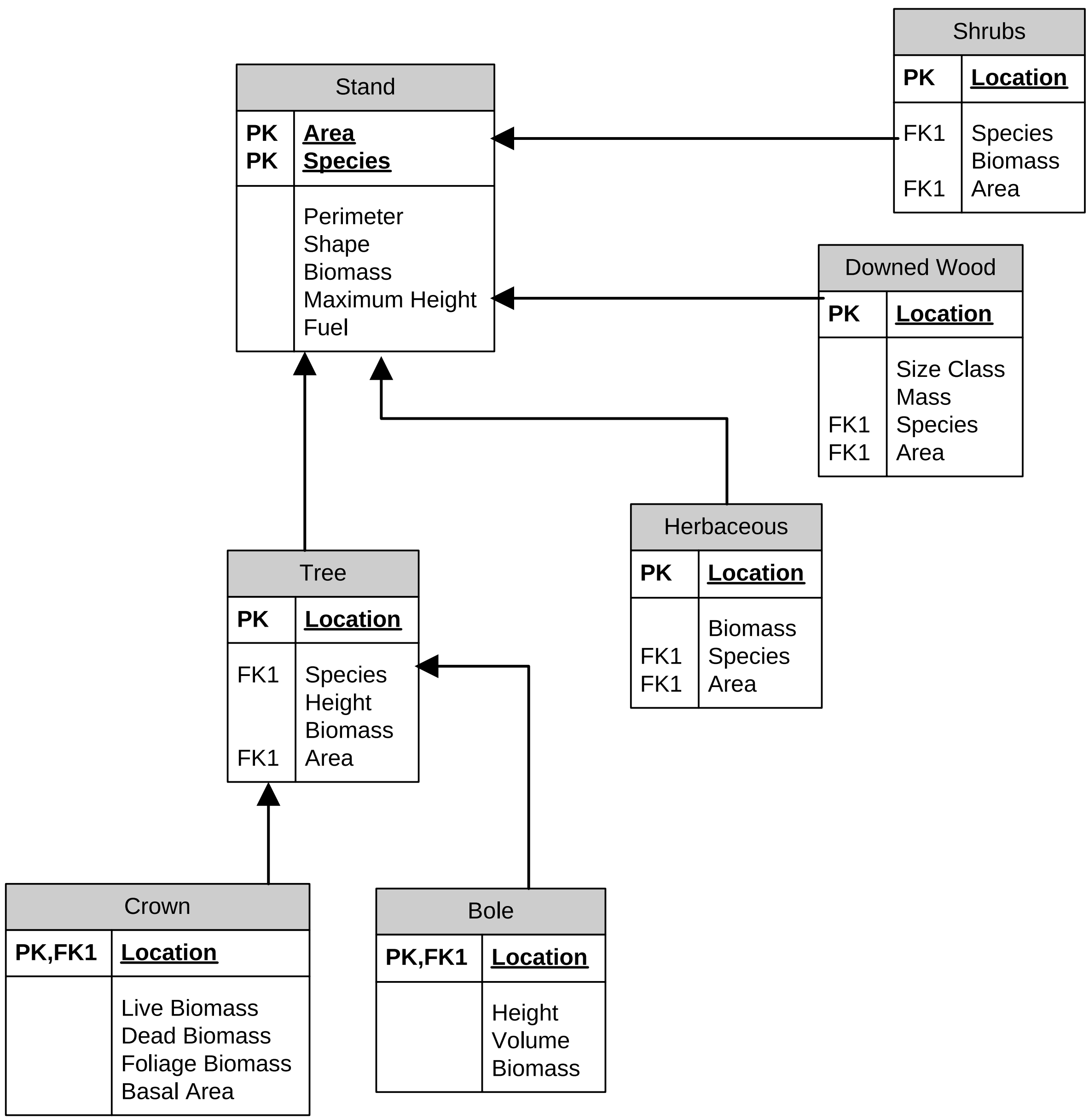


Figure 1. Data model for forest fuel descriptions derived from remotely sensed imagery

Currently, only some of this data model can be populated from remote sensing. For example, the data available from remotely sensed imagery do not distinguish live, dead, and foliage biomass in tree crowns, nor is basal area measured. Shrub and herbaceous layers and downed wood were also not measured. However, these may be capable of measurement in the future when a greater number of attributes for the data model can be populated.

The Data Model and Fire Models

The 10m pixel size of the radar imagery provides a very fine resolution for measurements of tree and fuel properties and this gives a very rich and detailed spatial description of variability in fuel properties for those variables that are measured. Similarly, environmental data, particularly topography, are available with a comparable high spatial resolution.

Although pixel-level data can be spatially aggregated and otherwise simplified to provide input to existing fire models, high spatial resolution remote sensing, as used here, as a data source for fuel property measurement fundamentally challenges many current fire models that have been developed with a particular set of environmental and fuel variables as inputs and with a different form of spatial representation (e.g. polygons). We envision that the opportunities provided by remote pixel-level measurement and representation of what is potentially a very large number of fuel properties will stimulate development of a new class of fire models.

Cellular models that operate on raster format data in GIS are an obvious candidate approach for novel fire models and could fully exploit the opportunities provided by remote sensing measurement of fuel properties. Cellular automata (CA), as a class of cellular model, operate on a regular grid that describes variability in one or more characteristics across space and explicitly include time dynamics as an element of processing. Since CA use a pixel-based representation they can use the data provided by remote sensing at its native (full) resolution. In CA, the change in state or condition of a pixel between time steps is defined by a series of rules[1] ('Rules' refer to conditional rules (e.g. if..then..else…) as well as equations and other functions that describe the relation between the start and subsequent condition or state of a cell.) that are applied based on both the attributes of a location and its neighbors. CA can use many input layers describing different attributes of a location and can thus include the full range of attributes documented in the data model. Because a CA can also consider the attributes of neighboring locations they excel at modeling diffusion processes. One CA model of fire spread currently exists, the HOT (Highly Optimized Tolerance) model from UCSB, but this uses different variables than developed in this project. A focused effort on CA modeling for fire spread and behavior linked to development of fuel properties from remote sensing would provide insight that would develop the new class of fire models we envision.

Cartographic Representation and Visualization

Remote sensing potentially provides extremely large volumes of data in terms of a) geographic area covered, b) minimum mapping unit or resolution (in the data provided here this is a spatial resolution of 10m x10m), c) in the measurement precision for variables, for example with radar data each pixel has a measured crown and bole biomass, and d) in the number of variables that describe fuel. Adequately representing these data presents a number of challenges that quickly exceed the capabilities of traditional representation using paper maps. The fine scale (resolution) detail is beyond the capability of paper maps to resolve, the information content of a map that presents data (as opposed to a generalized representation of the data) is too high for visual use, and since the continuous spatial representation of fuel properties provides little information that easily delimits homogenous areas, many alternate paper map realizations of a remotely sensed dataset are possible. Stand or species maps may provide spatial boundaries that can be used to generalize fuel data. These issues with paper map representation contrast with the opportunities provided by high spatial resolution imagery for numerical modeling of fire spread and computer-based exploration of the data using GIS in which individual values can readily be found.

The goal of this part of the project is to produce cartographic representations at 1:24,000 and 1:100,000 scales as maps that display both the detailed local content and regional summaries of the database in a format that can be used by fire managers.

Approach

Paper maps at each scale were produced by creating a simplified classification of fuel load based on generalized categories of biomass for the bole and crown layers from the radar data. The maps use a combined classification for the crown and bole data taken together to display at whether the biomass values are low/medium/high. This is considered to help to identify potential problem areas.

Each of the crown and biomass layers was reclassified using ESRI ArcGIS Spatial Analyst extension into three categories: low, medium, and high. The user is able to choose cutoff levels that identify low, medium and high biomass for the crown and bole very easily in ArcGIS; these can be absolute values selected independently of the data or can be based on the data. The bole and crown reclassification represents the two layers in simplified form with the following values for each layer

Bole.	Low: 1	Medium: 2	High: 3
Crown.	Low:10	Medium: 20	High: 30

After reclassification, the two layers are combined and the 1,2,3/10,20,30 values summed to produce a single classification including both layers. For example, a pixel with a high bole value and low crown value would have a combined value of 13. The resulting classes for the map are:

Crown	**Bole**
Low	Low
Medium	Low
High	Low
Low	Medium
Medium	Medium
High	Medium
Low	High
Medium	High
High	High

This combined classification identifies polygons sharing combinations of crown and bole biomass for presentation at 1:100,000 and 1:24,000 scales. Figures 2 and 3 illustrate the 1:100,000 scale and 1:24,000 scale maps respectively. Paper maps at each scale accompany this report.

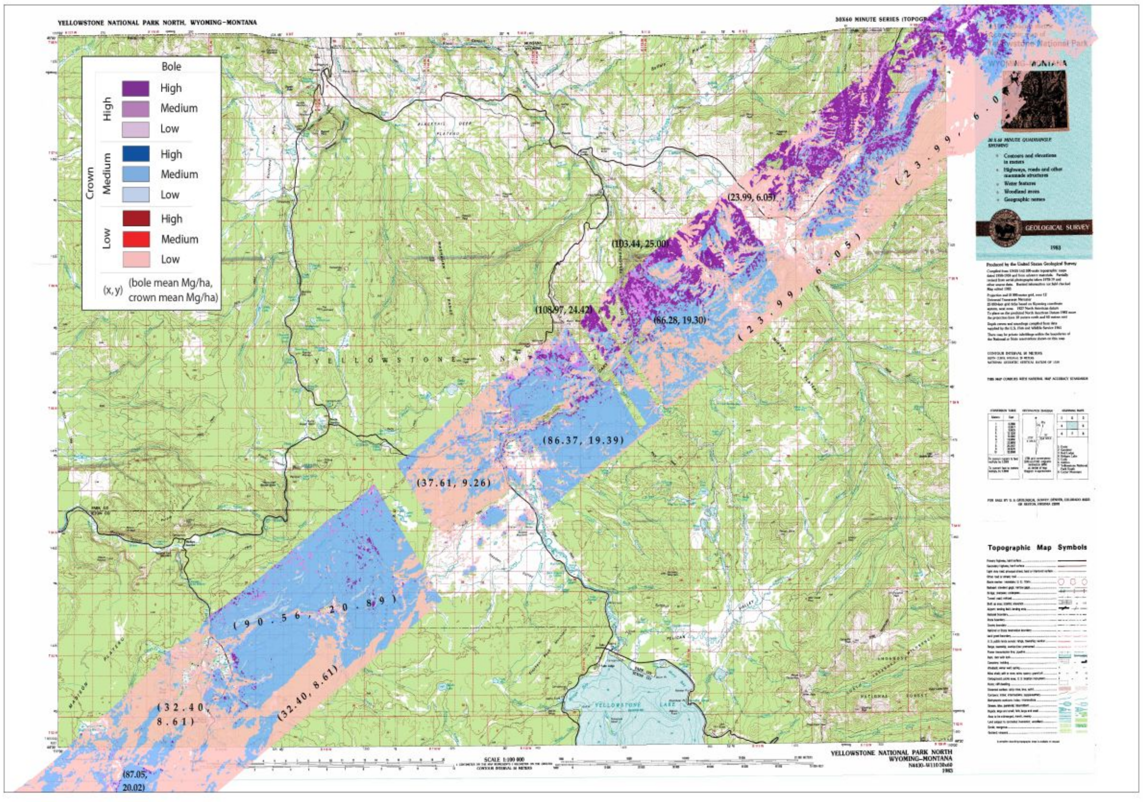


Figure 2. Illustration of the 1:100,000 scale map

Because this relatively simple process of generalization results in loss of a considerable amount of geographically local information about variation in biomass in each of the crown and bole, the map polygons are additionally labeled with their computed mean value for crown and bole biomass. Standard deviations, as a measure of variation within the generalized polygons can also be included. It is important to note that the mean values for polygons are calculated from the original data describing crown and bole biomass.

Limitations

Generalization always results in loss of information. Knowing what information is being lost is potentially important and we suggest that these simple processes for map production are best used interactively with fire managers.

Additionally, there remains hardware limitations associated with handling the very large data volumes derived from imagery. These are more considerable in GIS than in remote sensing software since the GIS adds topological and database properties to the data resulting in large processing and storage overheads. The file sizes we used limited the potential for automation of map production and labeling but smaller areas of interest or larger computers may ease this problem.

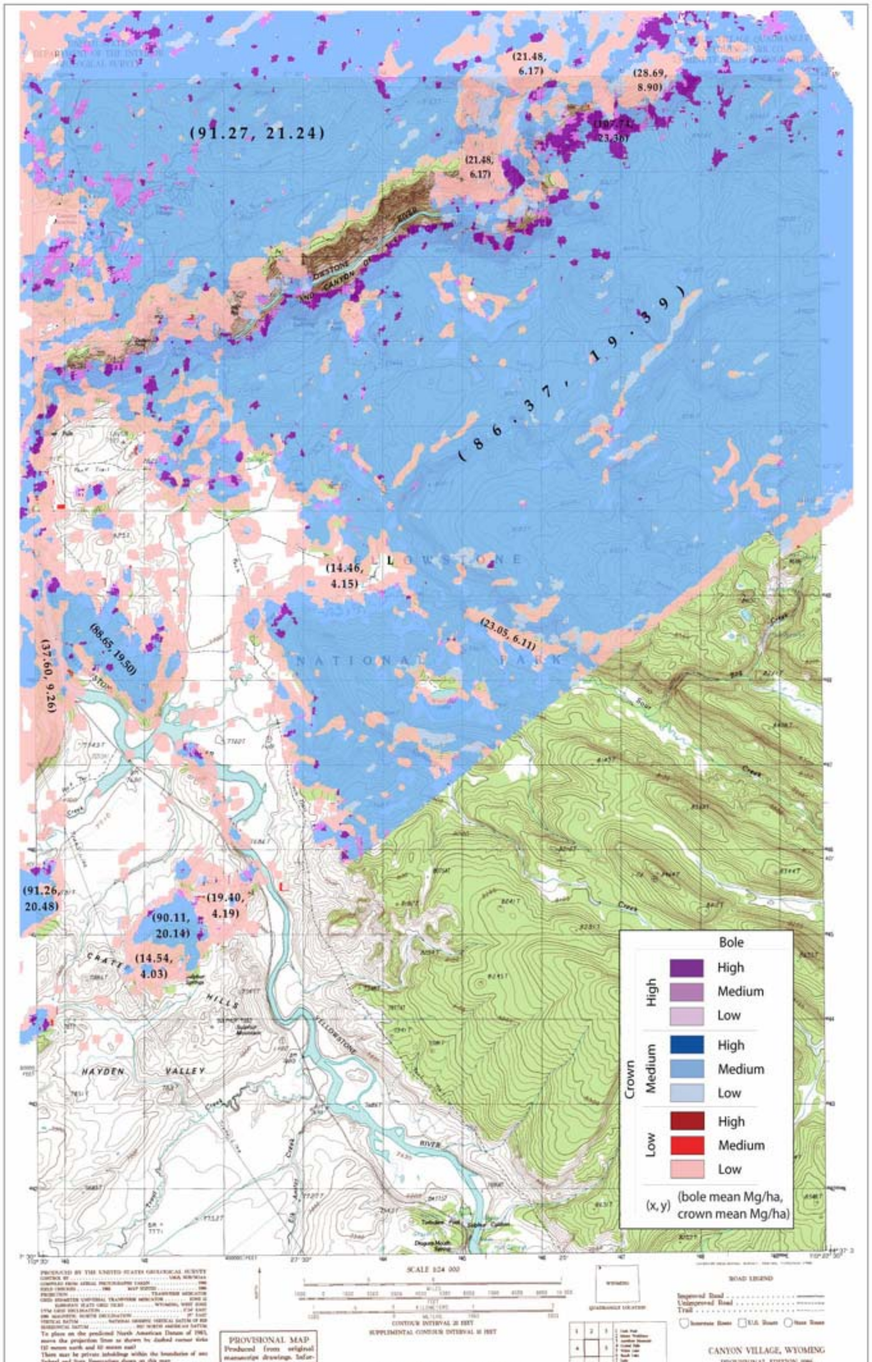


Figure 3. Illustration of 1:24,000 scale map

Suggested improvements

There are several alternate methods for mapping. One approach would be to use a vegetation type (species) data layer for the area (or stands or management blocks, as suggested in the data model) to identify homogenous areas. However, the vegetation datasets we examined did not show good agreement with the biomass data – biomass did not change in value in association with the mapped vegetation types. This may be the result of differences in date of data collection or inaccuracy in classification of vegetation types. A second approach is to use spatial analysis to explore neighborhood and zonal statistics to identify relatively homogenous areas to map as polygons. This typically leads to a very large number of small polygons (many are a single pixel in size) which presents problems in both interpretation of the maps and with file sizes. We conclude that the simple approach described above, applied interactively with fire managers, offers the best compromise between information content and computational tractability; the interactive process itself will also provide insights into the variability and values for fuel biomass across a study area and this will have benefits in understanding fuel distribution across landscapes.

Appendix I

Data Files

The following table provides a brief description of all data files provided as deliverables and currently available at the following FTP site: vesta.geog.ucsb.edu (username: anonymous, password: your email address) in the folder /pub/halligan. Files with no extension (or with the extensions '.flt' or '.map') are ENVI binary image files, filenames with '.hdr' extensions are ENVI header files. Files with the extension '.dsr' are ENVI density slice files which can be used to reconstruct the color scheme used to display ENVI images. Files with '.jpg' are JPEGs and '.jgw' are ESRI world files associated with those JPEGs, '.tif' are TIFF files or GeoTiffs, and '.tfw' are ESRI world files associated with a given TIFF (note that true GeoTiffs will not need this file, but some files here are TIFF not GeoTIFF format). Other file extensions include '.bmp' for Windows bitmap images, '.pdf' for Adobe compatible PDF files, '.xls' for Microsoft Excel files, and '.html' for HTML (web) files. Files with '.rar' extensions are compressed archive files which can be opened with Winzip, Winrar or other archive software.

airsar_10m_bole_class2.map	AIRSAR derived bole biomass (Mg/ha) binned into classes
airsar_10m_bole_class2.map.hdr	
airsar_10m_bole_class2.map_geotiff.tif	
airsar_10m_bole_class2.map_jpg.jgw	
airsar_10m_bole_class2.map_jpg.jpg	
airsar_10m_bole_final.flt	AIRSAR derived bole biomass (Mg/ha) - continuous values
airsar_10m_bole_final.flt.hdr	
airsar_10m_bole_final2.flt	
airsar_10m_bole_final2.flt.hdr	
airsar_10m_crown_class2.hdr	AIRSAR derived crown biomass (Mg/ha) binned into classes
airsar_10m_crown_class2.map	
airsar_10m_crown_class2.map_geotiff.tif	
airsar_10m_crown_class2.map_jpg.jgw	
airsar_10m_crown_class2.map_jpg.jpg	
airsar_10m_crown_final.flt	AIRSAR derived crown biomass (Mg/ha) coarse scale
airsar_10m_crown_final.hdr	
airsar_10m_crown_final2.flt	AIRSAR derived crown biomass (Mg/ha) fine scale
airsar_10m_crown_final2.hdr	
bole_biomass_classes_legend.jpg	JPEG of legend that matches airsar_10m_bole_class2.map
crown_biomass_classes_legend.jpg	JPEG of legend that matches airsar_10m_crown_class2.map
file_list.txt	text file listing all files on FTP site
fuels_sampling_protocol_2003.doc	Sampling protocol used for field data collection
hymap_airsar_Canyon_sub_RFclass100tree20var_maj3	HyMap and AIRSAR data fusion (level 2) result for the Canyon subset
hymap_airsar_Canyon_sub_RFclass100tree20var_maj3.hdr	
hymap_airsar_Canyon_sub_RFclass100tree20var_maj3_geotiff.tif	
hymap_airsar_Canyon_sub_RFclass100tree20var_maj3_jpg.jgw	
hymap_airsar_Canyon_sub_RFclass100tree20var_maj3_jpg.jpg	
hymap_airsar_NE_sub_RFclass100tree20var_maj3	HyMap and AIRSAR data fusion (level 2) result

hymap_airsar_NE_sub_RFclass100tree20var_maj3.hdr	for the NE Corner subset
hymap_airsar_NE_sub_RFclass100tree20var_maj3_geotiff.tif	
hymap_airsar_NE_sub_RFclass100tree20var_maj3_jpg.jgw	
hymap_airsar_NE_sub_RFclass100tree20var_maj3_jpg.jpg	
hymap_airsar_OF_sub_RFclass100tree20var_maj3	HyMap and AIRSAR data fusion (level 2) result for the Old Faithful subset
hymap_airsar_OF_sub_RFclass100tree20var_maj3.hdr	
hymap_airsar_OF_sub_RFclass100tree20var_maj3_geotiff.tif	
hymap_airsar_OF_sub_RFclass100tree20var_maj3_jpg.jgw	
hymap_airsar_OF_sub_RFclass100tree20var_maj3_jpg.jpg	
hymap_and_landsat_ML_class_key.bmp	NFFL fuel class legend for HyMap and Landsat ML classifications
HymapMLEclassX10kPlusAIRSARcrownFinal_geotiff.tfw	HyMap and AIRSAR data fusion (level 3) result for entire fusion subset
HymapMLEclassX10kPlusAIRSARcrownFinal_geotiff.tif	
HymapMLEclassX10kPlusAIRSARcrownFinal_legend.bmp	
HymapMLEclassX10kPlusAIRSARcrownFinal_masked	
HymapMLEclassX10kPlusAIRSARcrownFinal_masked.dsr	
HymapMLEclassX10kPlusAIRSARcrownFinal_masked.hdr	
hyper-sar_fusion_tables-figures1.pdf	PDF of figures and tables for data fusion (levels 1 and 2) results
hyper-sar_fusion_tables-figures2.pdf	
landsat_nffl70adjusted_masked	NFFL fuel models mapped on 1999 Landsat data using Maximum Likelihood classification and photo interp training points
landsat_nffl70adjusted_masked.hdr	
landsat_nffl70adjusted_masked_geotiff.tif	
landsat_nffl70adjusted_masked_jpg.jgw	
landsat_nffl70adjusted_masked_jpg.jpg	
landsat_sma.rar	Archive file containing Spectral Mixture Analysis results for Landsat 1999 image using field spectra as endmembers - shows fuel condition including fraction of live vs. dead vegetation
LandsatMLEclassX10kPlusAIRSARcrownFinal_legend.bmp	BMP file of legend that matches LandsatMLEclassX10kPlusAIRSARcrownFinal
LandsatMLEclassX10kPlusAIRSARcrownFinal_masked	Landsat (1999) and AIRSAR data fusion (level 3) result for entire fusion subset
LandsatMLEclassX10kPlusAIRSARcrownFinal_masked.dsr	
LandsatMLEclassX10kPlusAIRSARcrownFinal_masked.hdr	
LandsatMLEclassX10kPlusAIRSARcrownFinal_masked_geotiff.tfw	
LandsatMLEclassX10kPlusAIRSARcrownFinal_masked_geotiff.tif	
saatchi_fuel_body.pdf	Sassan Sattchi's AIRSAR manuscript - text
saatchi_fuel_figures.pdf	Sassan Sattchi's AIRSAR manuscript - figures
saatchi_fuel_tables.pdf	Sassan Sattchi's AIRSAR manuscript - tables
yerc_01-02_10m_mle	NFFL fuel models mapped using HyMap data and Maximum Likelihood classification and photo interp training points
yerc_01-02_10m_mle.hdr	
yerc_01-02_10m_mle_geotiff.tif	
yerc_01-02_10m_mle_jpg.jgw	
yerc_01-02_10m_mle_jpg.jpg	
yerc_02_10m_sma	Spectral Mixture Analysis results for HyMap imagery using field spectra as endmembers - shows fuel condition including fraction of live vs. dead vegetation
yerc_02_10m_sma.hdr	
yerc_03_10m_sma	
yerc_03_10m_sma.hdr	
yerc_03-04_10m_mle	NFFL fuel models mapped using HyMap data and Maximum Likelihood classification and photo interp training points
yerc_03-04_10m_mle.hdr	
yerc_03-04_10m_mle_geotiff.tif	
yerc_03-04_10m_mle_jpg.jgw	
yerc_03-04_10m_mle_jpg.jpg	

yerc_04_10m_sma yerc_04_10m_sma.hdr yerc_05_10m_sma yerc_05_10m_sma.hdr	Spectral Mixture Analysis results for HyMap imagery using field spectra as endmembers - shows fuel condition including fraction of live vs. dead vegetation
yerc_05-06_10m_mle yerc_05-06_10m_mle.hdr yerc_05-06_10m_mle_geotiff.tif yerc_05-06_10m_mle_jpg.jgw yerc_05-06_10m_mle_jpg.jpg	NFFL fuel models mapped using HyMap data and Maximum Likelihood classification and photo interp training points
yerc_06_10m_sma yerc_06_10m_sma.hdr yerc_07_10m_sma yerc_07_10m_sma.hdr	Spectral Mixture Analysis results for HyMap imagery using field spectra as endmembers - shows fuel condition including fraction of live vs. dead vegetation
yerc_07-08_10m_mle yerc_07-08_10m_mle.hdr yerc_07-08_10m_mle_geotiff.tif yerc_07-08_10m_mle_jpg.jgw yerc_07-08_10m_mle_jpg.jpg	NFFL fuel models mapped using HyMap data and Maximum Likelihood classification and photo interp training points
yerc_08_10m_sma yerc_08_10m_sma.hdr	Spectral Mixture Analysis results for HyMap imagery using field spectra as endmembers - shows fuel condition including fraction of live vs. dead vegetation
yfp_field_data.rar	Archive file containing field data including spreadsheet, shapefile for full dataset as well as an HTML page for each plot including photos
yogi_01_10m_sma yogi_01_10m_sma.hdr	Spectral Mixture Analysis results for HyMap imagery using field spectra as endmembers - shows fuel condition including fraction of live vs. dead vegetation
yogi_01-2b_10m_mle yogi_01-2b_10m_mle.hdr yogi_01-2b_10m_mle_geotiff.tif yogi_01-2b_10m_mle_jpg.jgw yogi_01-2b_10m_mle_jpg.jpg	NFFL fuel models mapped using HyMap data and Maximum Likelihood classification and photo interp training points
yogi_2b_10m_sma yogi_2b_10m_sma.hdr	Spectral Mixture Analysis results for HyMap imagery using field spectra as endmembers - shows fuel condition including fraction of live vs. dead vegetation

A table of RS data products and deliverable provided to USGS.

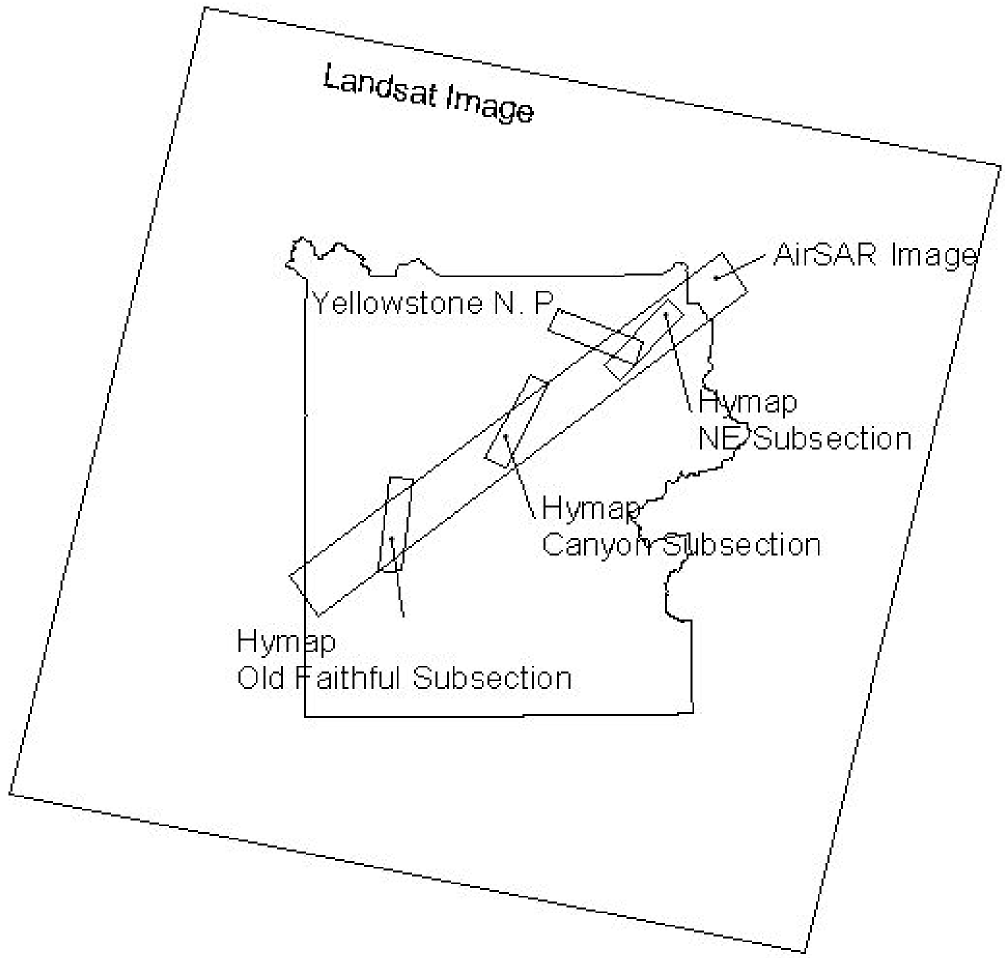
Appendix II

Deliverables Crosswalk Table

Proposed	Delivered	Status
Field-validated, high resolution fuel maps of the northern section of the Greater Yellowstone Ecosystem. These maps will be based on (a) fused multispectral and SAR data, and (b) fused, atmospherically corrected hyperspectral and terrain corrected SAR data. The maps will show vertical and horizontal distribution of consumable biomass according to vegetation species, including such items as vegetation type, fuel type, tree height, percent canopy cover, distribution of live versus dead vegetation, and total biomass and biomass components according to vegetation structure. The maps will be of immediate use to fire managers in Yellowstone National Park and the adjacent national forest units. Data products will provide valuable information to aid in the assessment of current stand conditions, management of fuels, fire prevention, and the direction of fire response. All products will be geo-referenced GIS layers (ARC/INFO format	AIRSAR derived bole biomass (Mg/ha) binned into classes	Done
	AIRSAR derived bole biomass (Mg/ha) - continuous values	Done
	AIRSAR derived crown biomass (Mg/ha) binned into classes	Done
	AIRSAR derived crown biomass (Mg/ha) coarse scale	Done
	AIRSAR derived crown biomass (Mg/ha) fine scale	Done
	HyMap and AIRSAR data fusion (level 2) result for the Canyon subset	Done
	HyMap and AIRSAR data fusion (level 2) result for the NE Corner subset	Done
	HyMap and AIRSAR data fusion (level 2) result for the Old Faithful subset	Done
	HyMap and AIRSAR data fusion (level 3) result for entire fusion subset	Done
	NFFL fuel models mapped on 1999 Landsat data using Maximum Likelihood classification and photo interp training points	Done
	Landsat (1999) and AIRSAR data fusion (level 3) result for entire fusion subset	Done
	NFFL fuel models mapped using HyMap data and Maximum Likelihood classification and photo interp training points	Done
	Spectral Mixture Analysis results for HyMap imagery using field spectra as endmembers - shows fuel condition including fraction of live vs. dead vegetation	Done
	NFFL fuel models mapped using HyMap data and Maximum Likelihood classification and photo interp training points	Done
	Spectral Mixture Analysis results for HyMap imagery using field spectra as endmembers - shows fuel condition including fraction of live vs. dead	Done

	vegetation NFFL fuel models mapped using HyMap data and Maximum Likelihood classification and photo interp training points Combined crown and bole biomass, 1:100,000 Combined crown and bole biomass, 1:24,000	Done Done
<u>Precise, field-validated algorithms and processes</u> for creating fuel maps at scales suitable for operational fuel and fire management programs. The algorithms will include terrain correction, sensor fusion, and GIS data modeling, and focus most strongly on SAR and hyperspectral data. These algorithms will allow accurate, efficient evaluation of wildland fuel and fire/hazard parameters across a wide range of ecological settings. Outputs from the algorithms will be directly compatible with existing fire models. Because the study area includes a wide variety of vegetation types, terrain conditions, and fuel loadings, the algorithm and processes developed for the study area should be usable over much of the western US.	VIPER tools • SA Create Spectral Libraries • Manage Spectral Libraries • Select Optimal Endmembers for SMA • Knowledge-based Endmember Selection • Calculate SMA Fractions and Determine Best-fit Models • Post-process SMA/MESMA Results R terrain correction Three fusion algorithms • Level 1 • Level 2 • Level 3 NFFL classification models	Done Done Done Done
<u>A decision matrix table</u> capable of assisting wildland managers in determining the relative cost versus comparative	Table shown on page 12	Done

utility of selecting remotely sensed data of high and low levels of spatial and spectral resolution, plus the applicability of terrain correction and sensor fusion for discriminating the key fire/fuel parameters shown in Table 6. The matrix will be derived from test case fuel maps created for subsections of the study area that involve differing landscapes, fuel loading, and cover type. The decision matrix will include such items as species identification, land cover type determination, prediction of vertical and horizontal biomass distribution, userability, relative cost, and time and complexity of fuel map creation. Along with the decision matrix, we will provide recommendations to wildland managers on selecting the appropriate data requirements for the intended mapping application, and on the cost-effectiveness and utility of different remote sensing data types and methods for various fuel-management applications.		



Index of map products listed in the Crosswalk Table. The different sensor's footprints are shown. Maps using multiple sensors cover the intersection of the different sensors.