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Mapping of land cover in northern California with simulated hyperspectral satellite imagery

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ABSTRACT

Land-cover maps are important science products needed for natural resource and ecosystem service management, biodiversity conservation planning, and assessing human-induced and natural drivers of land change. Analysis of hyperspectral, or imaging spectrometer, imagery has shown an impressive capacity to map a wide range of natural and anthropogenic land cover. Applications have been mostly with single-date imagery from relatively small spatial extents. Future hyperspectral satellites will provide imagery at greater spatial and temporal scales, and there is a need to assess techniques for mapping land cover with these data. Here we used simulated multi-temporal HyspIRI satellite imagery over a 30,000 km^2 area in the San Francisco Bay Area, California to assess its capabilities for mapping classes defined by the international Land Cover Classification System (LCCS). We employed a mapping methodology and analysis framework that is applicable to regional and global scales. We used the Random Forests classifier with three sets of predictor variables (reflectance, MNF, hyperspectral metrics), two temporal resolutions (summer, spring-summer-fall), two sample scales (pixel, polygon) and two levels of classification complexity (12, 20 classes). Hyperspectral metrics provided a 16.4–21.8% and 3.1–6.7% increase in overall accuracy relative to MNF and reflectance bands, respectively, depending on pixel or polygon scales of analysis. Multi-temporal metrics improved overall accuracy by 0.9–3.1% over summer metrics, yet increases were only significant at the pixel scale of analysis. Overall accuracy at pixel scales was 72.2% (Kappa 0.70) with three seasons of metrics. Anthropogenic and homogenous natural vegetation classes had relatively high confidence and producer and user accuracies were over 70%; in comparison, woodland and forest classes had considerable confusion. We next focused on plant functional types with relatively pure spectra by removing open-canopy shrublands, woodlands and mixed forests from the classification. This 12-class map had significantly improved accuracy of 85.1% (Kappa 0.83) and most classes had over 70% producer and user accuracies. Finally, we summarized important metrics from the multi-temporal Random Forests to infer the underlying chemical and structural properties that best discriminated our land-cover classes across seasons.

1. Introduction

Land-cover maps are important science products needed for natural resource and ecosystem service management, biodiversity and conservation planning, and understanding human-induced and natural drivers of land change. Most land-cover maps at regional to global scales are produced with remote sensing techniques applied to multi-spectral and multi-temporal satellite imagery, such as 30-m Landsat imagery (Hansen et al., 2013; Homer et al., 2015; Wulder et al., 2012) or 250–500 m MODIS imagery (Clark et al., 2012; Friedl et al., 2010). Hyperspectral, or imaging spectrometer, sensors have shown an impressive capacity to map a wide range of land cover. Applications focused on natural land cover include individual plant species, vegetation lifeforms and forest type (Clark and Roberts, 2012; Dalponte et al., 2012; Dennison and Roberts, 2003; Fagan et al., 2015; Roth et al., 2015; Schaaf et al., 2011) and anthropogenic land cover such as crops, plantations and urban vegetation and materials (Fagan et al., 2015; Franke et al., 2009; Ghosh et al., 2014).

Hyperspectral land-cover mapping research has mostly focused on relatively small spatial extents (<1000 km^2) with strips of single date imagery. Notable exceptions include: a recent study by Roth et al. (2015), who analyzed a total of ~11,000 km^2 (including water) of NASA's Airborne Visible Infrared Imaging Spectrometer (AVIRIS) imagery over five separate sites in the United States for

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mapping plant species and other land cover types; and, vegetation studies that have explored the temporal domain with multiple dates of AVIRIS airborne (Dennison and Roberts, 2003; Dudley et al., 2015) and Hyperion satellite (Saini et al., 2014; Somers and Asner, 2013) imagery. Given the high costs and accessibility limitations with airborne data acquisition, only space-based sensors will permit hyperspectral research to expand to the regional to global spatial scales that have been reserved for multi-spectral satellites. Fortunately, there are next-generation hyperspectral satellites on the horizon, including the German Environmental Mapping and Analysis Program (EnMap; Guanter et al., 2015), Japanese Hyperspectral Imager Suite (HISUI; Matsunaga et al., 2014), and the United States Hyperspectral Infrared Imager (HyspIRI; Lee et al., 2015). These satellite missions will provide global 30-m imagery with 16–27 day repeat acquisitions and have sensors that cover visible to shortwave infrared regions (VSWIR: 380–2500 nm) with considerably higher signal-to-noise (SNR) than the Hyperion satellite, which is nearing the end of its extended 15-year mission.

There is an acute need to test existing, and develop new, analytical methods for land-cover mapping with hyperspectral data at the expanded spatial and temporal scales provided by future satellites. Conventional parametric classifiers used to map land cover from multi-spectral imagery, such as Maximum Likelihood, fail to separate classes with internal variability and are problematic with high dimensionality data (Duda and Hart, 1973). Spectral mixture analysis (SMA) with iterative cycles of endmember selection, such as multiple-endmember spectral mixture analysis (MESMA) and automatic Monte Carlo unmixing (AutoMCU), are popular hyperspectral classifiers that can accommodate land-cover types with some spectral and temporal variability (reviewed in Somers et al., 2011). These techniques have been used to map natural and anthropogenic land cover at a sub-pixel level, and are most effective when spectrally-pure image endmembers, such as individual species or particular urban materials, can be identified in high spatial resolution imagery (i.e., less than 30 m) – typically in connection with field surveys. Most SMA studies are local in scale (<1000 km^2) with site-specific classes, and have not mapped standardized land-use/cover types needed at global scales, such as those defined by the U.N. FAO Land Cover Classification System (LCCS). There are several limitations to SMA that may limit its broader appeal when used with hyperspectral satellite data, including: a wide variety of under-tested techniques and user parameters; difficulty in finding spectrally-pure image endmembers from moderate resolution pixels; large spectral libraries to accommodate higher spectral and temporal variability; and, significantly long processing times (Roberts et al., 2003; Somers et al., 2011). Whereas MESMA performs a time-intensive, exhaustive search of all possible endmember models in unmixing each image pixel, new SMA techniques use linear sparse regression to speed selection of optimal endmembers from large libraries (Iordache et al., 2011). The latest advances include using the spatial autocorrelation structure in image spectra to improve sparse regression solutions (Feng et al., 2015; Zhong et al., 2014). However, these techniques have been tested only with lab and field spectral libraries applied to simulated images and a small area of AVIRIS data with minimal vegetation (Cuprite, Nevada). It is not yet clear how these techniques will perform across larger terrestrial areas where lab/field spectral libraries are limited and images have higher spectral variability.

Alternatively, machine learning classifiers are non-parametric, supervised algorithms that may overcome some of the difficulties with SMA. A popular algorithm is Random Forests (RF), which has shown promise in land-cover mapping studies with multispectral (Clark et al., 2012; Magdon et al., 2014; Rodriguez-Galiano et al., 2012), hyperspectral (Burai et al., 2015; Clark and Roberts, 2012; Fagan et al., 2015; Ghosh et al., 2014), and multi-temporal (Clark et al., 2012; Fagan et al., 2015) imagery. For example, RF has been used to map LCCS classes from time series of MODIS imagery over the Kalahari region in Namibia (Hüttich et al., 2011). Random Forests has several advantages in land-cover mapping at broad spatial scales, including its: ability to accommodate the diversity of spectral-temporal response in broad land-cover classes over large areas; speed at training and map classification; few user-defined parameters or intervention; and, low sensitivity to training data predictor dimensionality, class size and error (see Rodriguez-Galiano et al., 2012). Research with RF in hyperspectral research is limited, and to our knowledge includes no multi-temporal or LCCS mapping applications.

The broad goal of this study is to estimate the accuracy of multi-temporal, HyspIRI-like imagery for mapping of land cover across a range of environmental and anthropogenic gradients in the San Francisco Bay Area of California. We designed our study by testing data and methods that could scale to include global and seasonal imagery provided by a hyperspectral satellite. Our method includes reference data collected using visual interpretation of high-resolution imagery in Google Earth; a discrete classification scheme that follows LCCS rules; the RF classifier; image data from three seasons; and, analysis constrained to the spatial scale, radiometric fidelity, and atmospheric correction expected from HyspIRI satellite imagery. There are inconclusive results about the efficacy of variable transformation as input to the RF classifier (Burai et al., 2015; Clark and Roberts, 2012; Fagan et al., 2015; Ghosh et al., 2014). Here we transform reflectance data into Minimum Noise Fraction (MNF) bands and a suite of hyperspectral metrics as sets of predictor variables. For each group of predictor variables (reflectance bands, MNF bands, and metrics), our accuracy assessment compared temporal resolution (summer and three-season), sample scale (pixel and polygon) and, classification complexity (20 and 12 LCCS classes).

2. Methods

2.1. Study area

Imagery in this study covered a box centered (37°52′45.73″N, 122°13′8.54″W) on the San Francisco Bay Area in northern California, USA (Fig.1). This area includes the Temperate Coniferous forests biome in the north (ecoregion California North Coast) and the Mediterranean Forests, Woodlands, and Scrub forests biome to the south (ecoregions California Central Coast and Great Central Valley). The region has a mostly Mediterranean climate with average annual precipitation of 689 mm, and a seasonal average of 162 mm in spring [March – May], 6 mm in summer [June – August], 123 mm in fall [September – November], and 397 mm in winter [December through February] (NOAA, 1981–2010 U.S. Climate Normals: Ground stations within box). Average minimum and maximum temperatures are 9 °C and 21 °C, respectively. There is a range of fine-scale variation in climate across the study area largely determined by distance from coast and topography as a marine air mass and advection fog moderates annual climate variability by providing summer moisture and cooler temperatures along the coast and adjacent low-elevation areas that it penetrates; and consequently, annual precipitation tends to be higher toward the coast and in the north and summer temperatures tend to be highest and winter temperatures lowest in the east.

Natural vegetation in the study area is largely determined by fine-scale variability in climate, interlinked with topographic controls (elevation, position, aspect) and coastal influence, as well as variation in soils and disturbance. In general, evergreen needleleaf forests (conifer) and evergreen broadleaf forests are mainly in the west; in the interior mountains, deciduous broadleaf forests inter-