Spatially quantifying and attributing 17 years of vegetation and land cover transitions across Hawai`i

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Aloha to all!

Abstract

Hawaii has seen widespread land use change and large scale land cover shifts. However, this is only known either anecdotally or from a single locale studies. Therefore little information exists on the rate or extent of land cover change across Hawaii. As such, this project produced statewide annual maps from 1999 to 2016 of percent cover of forest, grass and bare earth, from LANDSAT imagery, and attributed change to a spatial dataset of land management history. Statewide net change resulted in a gain in woody cover primarily occurring in unmanaged areas and abandoned agricultural land. These findings suggest that Hawaii is going through a forest transition, primarily driven by agricultural abandonment and probable invasive species expansion, with additional inputs from forestry production in areas with potential for native forest restoration. This work is aids in a better understanding of the direct land cover consequences from land use changes in Hawaii.

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Introduction:

Anthropogenic land cover change is causing far-reaching alterations to the functioning and processes of world ecosystems (Vitousek et.al 1997). Around 50% of the earth's land surface has undergone a human alteration resulting in land cover change (Foley et.al 2005). Land use directly alters the structure and function of ecosystems (and ultimately, the global system) which affects the human system beyond the immediate land use (Foley et.al 2005, Turner, et.al 2007, Haberl el.al 2007). To understand the cause of land cover change, it's impacts on global resources and ecosystem services, it is also essential to examine the broader context and role of land use decisions (Turner, et.al 2007). For example, in recent decades agricultural production areas (i.e., croplands, pastures, plantations), and urban areas (Foley et.al 2005) has expanded globally, increasing demands for additional resources such as energy, water, and fertilizer (Foley et.al 2005, Haberl et.al 2007).

These additional land and resource demands have resulted in severe global landcover changes in areas with significant global ecosystem services, particular tropical forest. During the 1990's it is estimated that 1-2 PgC/yr of carbon has been released due to global deforestation (Houghton et.al 2005). From 2000-2012 it was observed that tropical forest loss continued thus increasing to 2101 square kilometers per year globally (Hansen et. al 2013). These ongoing losses in these species rich hotspots have had sever negative impacts on biodiversity (Brooks, et al. 2002) and continue to contribute additional carbon into the atmosphere (Pan et.al 2011). Given the drastic outcomes of these land cover changes the importance of assessing large scale land cover changes is of serious importance for ultimately understanding the proximal and distal land use drivers.

Fortunately the technical ability to track the patterns of land use and land cover change over large spatial and long temporal scales is rapidly developing due to improved satellite image availability and quality, and access to powerful computational resources (Hansen et.al 2013). However knowledge of local and regional land use histories are critical to understanding drivers of doccumented changes, much of which can often produce counterintuitive outcomes (Lambin et.al 2001). Often analyses at the global scale are likely to gloss over the complex and regionally-important causes and drivers of land cover change.

For example, while the world has suffered a net loss in forest cover since 2000 (Hansen, 2013), several countries have shifted from net deforestation to net reforestation (Meyfroidt et.al 2011). In the latter half of the 20th century Puerto Rican forests increased from 9% to 37% of the island's land area (Rudel et.al 2000). This was mainly attributable to a decline in smallholder agriculture lots in upland areas, allowing for natural transition back to forest (Rudel et.al 2000). In the Atlantic forests of Argentina, overall forest cover loss halted as well, but only because of increasing of plantation forestry, a land use with much lower biodiversity value than the natural forest of the region (Izquierdo et.al 2008). These "forest transitions" provide examples of land cover change dynamics that are the result of departures from past land use actions or transition to new land use attributed to economic or social changes (Meyfroidt et.al 2011).

Land cover change mechanisms are often a complex interplay of anthropogenic land use, land cover change as well as direct and indirect influences on the frequency and severity of change (Lepers et.al, 2005). For example, human caused changes in fire regimes contribute to the degradation of tropical forests. In Borneo, increased deforestation from 2002 and 2005 was highly correlated with fire disturbance at forest edges (Langner et.al 2007). Forest fires are growing in size and frequency across the tropics, and potentially affect millions of people through changes in landscapes, health and contribution to climate change intensification, all of which may feedback into more increased fire and potential landcover change (Cochrane 2003). Other indirect feedbacks such as invasive species spread and their ability to further alter disturbance regimes, such as fires, can further complicate change dynamics (Mack et.al 1998).

Land use change, disturbance, and invasive species are key causes of land cover change on islands (D'Antonio and Vitousek 1992, Neill and Rea 2004, Ellsworth 2014). In Hawaii, agricultural decline (Perroy et.al 2016), increasing commercial forestry (Ares et.al 2000), and human housing development have been identified as important causes of land cover change in recent decades. Invasive species, alter ecosystem function and composition (Scowcroft et.al 1983, Vitousek et.al 1989, Hughes et.al 2005, Litton et.al 2006) and disturbance regimes (Trauernicht et.al 2015), and are widely established across the state (Asner et.al 2008). Multiple conservation and restoration projects aim to preserve intact native ecosystems (Hawaii Conservation Alliance 2005) and/or rehabilitate degraded lands to increase native vegetation cover (Scowcroft et.al 1999, Medieros et.al 2005). While numerous studies in Hawaii have documented site-level transitions in vegetation cover and composition (Hughes et.al 2005, Leary et.al 2006, Litton et.al 2006), the extent and rates of land cover transformation are typically only available from anecdotal accounts based on local knowledge of land users and managers (Ellsworth 2014). Quantifying landscape scale cover changes in Hawaii is critical to assessing and monitoring ecosystem condition and the services they provide (Cadenasso et.al 2001) as well as the outcomes of land use and management actions.

While several land cover products have been created for Hawaii from remotely sensed imagery (e.g, LANDSAT), these efforts either provide just a single land cover map in time (HI GAP Analysis Program), or update land use and vegetation cover change in an ad hoc manner, based on assumed outcomes of known events such as all burned areas resulting in grass expansion (LANDFIRE 2008) or adding urban/suburban development in known areas without changing vegetation dynamics in remote areas (Coastal Change Analysis Program C-CAP). In addition, these products are derived from remote sensing methods that classify pixels into distinct classes (Congalton et.al 1991), thereby restricting cover information to discrete categories at the resolution of the imagery. In reality, however, pixels often contain more than one land cover type. If land cover and vegetation types are highly variable across space and occurring at small scales across the landscape, or, land cover is heterogeneous at the sub-pixel level, meaning sub-pixel conditions may not be detected and/or could easily be misclassified.

Thus, current preclude accurately quantifying the extent and degree of land cover change in Hawaii. Alternatively, spectral unmixing is a remote sensing method that can calculate approximate amounts of defined cover types within single pixels in an image (Keshava, et al. 2003). spectral unmixing aims to address this problem of discrete data classification by converting band radiance/reflectance values to fractional cover estimates of ground based features. Essentially, spectral unmixing defines the composition of image pixels by estimating proportions of mixed cover types using mathematical relationships of known "pure" cover to spectra observed from satellite sensors. Further, once these spectra are identified, spectral unmixing can be applied at annual or intra-annual time steps. Measurement of continuous, subpixel land cover proportions over time allows for statistical trend analyses that can identify the extent and rates of land cover change and attribute these changes to processes on the ground.

Numerous unmixing methods exist and have been applied to a wide range of natural resources and environmental monitoring, albeit with many examples relying on hyperspectral imagery and complex nonlinear unmixing algorithms (Keshava, et al. 2003; Quintano, et al. 2012). The simplest unmixing algorithm is linear spectral unmixing, which uses an inverse ordinary least squares model to spectrally unmix an image scene into proportions (Keshava, et al. 2003). Several studies have demonstrated that linear unmixing analysis can accurately be applied to multispectral

LANDSAT imagery. For example, linear unmixing of LANDSAT imagery has been used to measure subpixel estimates of canopy closure of California oak woodland savanna (Pu, et al. 2003), fire severity and recovery in North American Pine forest (Smith, et al. 2007), and vegetation dynamics in Mediterranean rangelands (Hostert, et al. 2003). The use of spectral linear unmixing enables conversion of LANDSAT spectra into ecologically relevant estimates of subpixel vegetation cover that facilitate measuring land cover change in Hawaii.

In Hawaii it is unclear: *How much of land cover is changing?, Where is change occurring? How fast is change happening? and, What are the current cover outcomes from change?* Addressing these questions will (i) improve the understanding of the how land cover is changing in Hawaii and is impacted by land use dynamics, (ii) provide a tool for researchers, managers and decision makers to evaluate current and potential future landscape scale drivers of land cover change.

This study applied spectral unmixing on archived LANDSAT 7 data, to assess statewide vegetation/cover change in Hawaii by (i) creating sub-30m-pixel fractional cover estimates of three dominant vegetation/covers (forest/coarse vegetation, grass/fine vegetation, & bare earth) thus providing spatially and temporally continuous annual maps of Hawaii for the 17 years studied; (ii) identifying areas of vegetation/cover shifts; and (iii) quantifying gross vegetation/cover outcomes in losses and gains. The research also attempts to attribute land cover changes to potential causes by compiling several existing spatial datasets of past and current land use change, zoning, fire history and conservation management efforts.

Methods:

Overview

This research used a linear spectral unmixing model based on archived LANDSAT 7 images of the main Hawaiian Islands to calculate statewide, fractional cover estimates of three broad cover classes: woody (i.e., trees and/or dense woody vegetation), grass (i.e, herbaceous/fine vegetation) and bare earth. These classes were selected because they represent vegetation cover classes that are present and ecologically appropriate and statewide. For the purpose of this study woody/coarse vegetation cover is defined as all green (photosynthetically active) dense woody vegetation taller than 5m in height. Grass cover (i.e, herbaceous/fine vegetation) is defined as dry (non- photosynthetically active) low-lying fine woody vegetation as well as all green or dry nonwoody herbaceous vegetation including forbs, ferns, and graminoids. Bare earth is all non-vegetated land surface and is intended to include a wide range of soil series and ages found across Hawaii ranging from young bare lava flows to aged weathered oxisoils and andisols. To perform linear spectral unmixing we first identified endmembers, or the unique spectral characteristics that define these cover classes across the pixels that comprise an image. The method used to train the unmixing algorithm was by obtaining endmember spectra from areas that are confirmed to have 100% cover of each land cover class (Keshava, et al. 2003). These "pure" pixels must are represented across the image scene, and should be spectrally unique and for purposes of this study ecologically applicable. The confirmation of these "pure pixels" requires pixels that have been validated to contain only one type of endmember cover class and as such can be used to spectrally describe the endmember across the image.

The study area included all land surface area for the eight main Hawaiian Islands including Hawaii, Maui, Kooahlawe, Lanai, Molokai, Oahu, Kauai and Niihau islands. The total area of this study was approximately 15800 km^2 (6100 $miles^2$) Alpine areas above 3350 meters (approximately 11,000 Ft) were excluded from analysis, due to known unchanged bare extent and matchless geologic substrates. Some bare area pure pixels from these high elevation regions contributed to the training dataset. Furthermore, known areas of currently cultivated agriculture, as identified by Perroy et.al 2016, were also excluded from the study as it was not the intended focus of this study and the high production plant growth along with cultivation cycles (growth and harvest) are not calibrated in this unmixing and change detection application.

This analysis used the entire available LANDSAT 7 image archive from 1999-2016 and was performed with custom remote sensing processing and statistical trend analysis codes in the Google Earth Engine (GEE) cloud-based remote sensing and GIS platform (Google Earth Engine Team, 2015). LANDSAT 7 did not collect images of oceanic islands in 2014, but resumed collection in 2015 and 2016, given the amount of data before and after 2014 we feel this method is valid for the entire study period. The GEE workflow included several steps including: (i) creating cloud free statewide image composites, (ii) automating the separation and classification of landcover into "green" and "dry" areas , (iii) unmixing of four endmember (including "green" and "dry" grass/ fine vegetation) fractional covers across multiple temporal composite images, (iv) combine "green" and "dry" grass/ fine vegetation cover in one grass/ fine vegetation, (v) creating annual continuous coverage mosaic images from seasonal fractional cover images of per pixel (30m x 30m) percent bare, percent grass/herb, and percent forest/woody cover, (vi) performing regression analyses of change in covers over time across all pixels (N=18,000,000) to identify “real change” pixels, and (vii) measuring “real change” pixels’ rates of cover change, total area changing, and modeled cover outcomes within these spatial land-use “causes” statewide and within each island. Each of these steps is expanded upon in the following sections.

Endmember Selection Confirmation of Pure-Pixel Locations

In order to perform spectral linear unmixing, we chose spectrally unique and present endmembers to decompose the sub-pixel fractional estimates. For Hawaii, the three most dominant broad land covers (from HI GAP land cover product “cover” class) are forest (coarse vegetation), grassland (fine vegetation), and bare earth. The wide spread nature of these covers and their confirmed spectral uniqueness (figure 1, 2 & 3), indicates unmixing of theses endmembers from a statewide composite image should be possible. Furthermore, once grass/fine vegetation is split into “dry” and “green” classifications, inspection of these class’s spectra indication their spectral separability (figure 1 & figure 2).

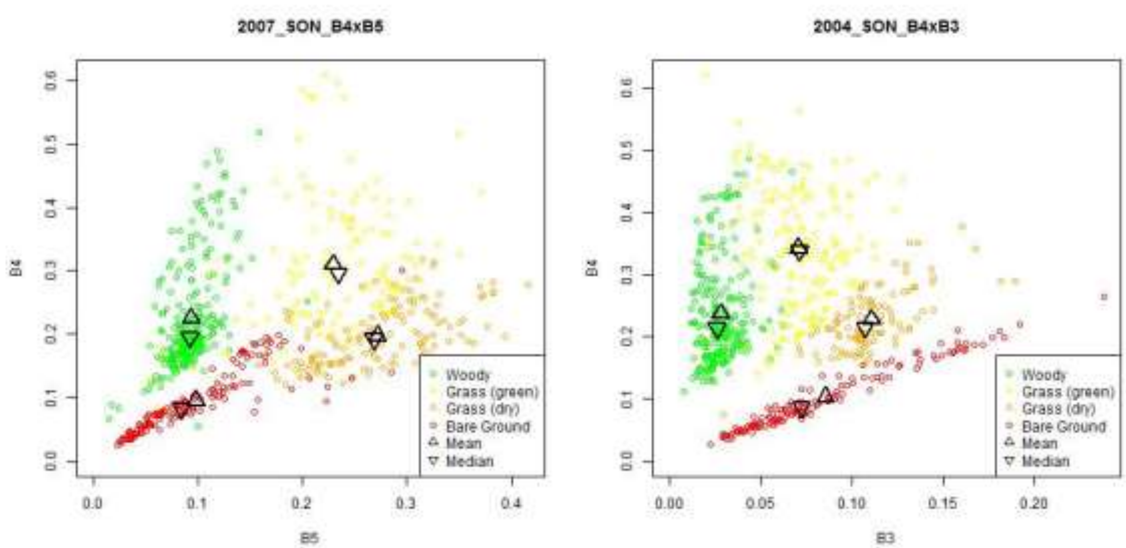

Figure 1: Bi-spectral plots of 4 endmember classes with mean (up triangle) and median (down triangle) (L) 3 month mean composite image SON 2007 Band 4 over Band 5 (R) 3 month mean composite image SON 2004 Band 4 over Band 5

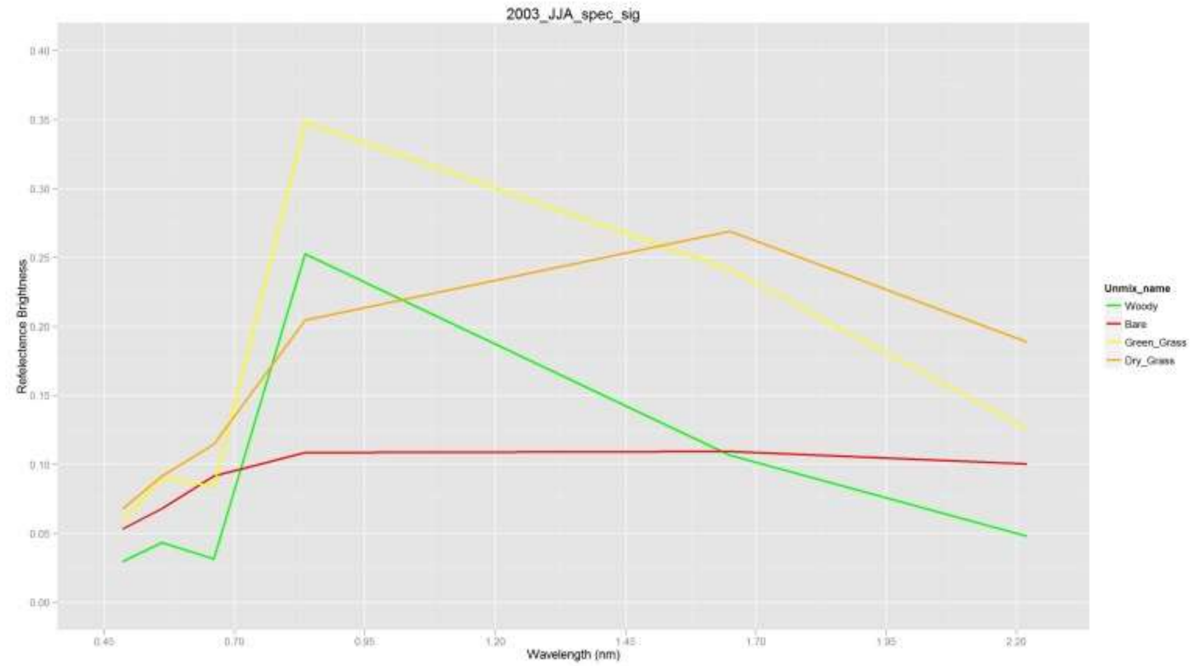

Figure 2: Spectral signature 4 endmember classes for 3 month mean composite image (June, July, Aug, 2003)

For this study acceptable "pure pixels" needed to be areas of continuous cover of each of the final fractional cover classes, which have remained relatively unchanged during the period of study. To identify pure pixel endmembers, random locations of 100 m x 100 m (>3x3 LANDSAT cells) pure pixel 'plots' were created within core areas (>90m from edge) of three broad land cover classifications (bare earth, grass/herb/fine vegetation, and forest/woody/coarse vegetation) from 2000, HI Gap land cover product. These locations were confirmed or rejected using the online high resolution, 5-way orthographic aerial imagery of Pictometry ™ (www.pictometry.com).   of Pictometry ™ imagery for Hawaii provides nearly statewide coverage begging in 2008 onward with biennial re-image capture for most areas until 2015. Confirmation as a pure unchanged location required that the plot contained pure cover at the later date of the Pictometry ™ observation and that this cover agreed with the classified cover of the earlier 2000 HI gap product (figure 3). Overall 872 potential pure pixel locations were examined and 561 pure pixel plots (265 (bare earth, grass/herb/fine vegetation, and forest/woody/coarse vegetation), 183 grass/herb/fine vegetation, 113 bare earth) were confirmed statewide (figure 3). Fine vegetation cover, such as grass, is highly sensitive to phenological changes due to moisture availability (Archibald and Scholes 2007, Lucas et al 2017). To later account for this and because different phenological conditions of fine vegetation, such as grass, Pictometry ™observations of grass cover also included visual confirmation of "photosynthetic/green" and "non-photosynthetic/dry" at the time of observation.

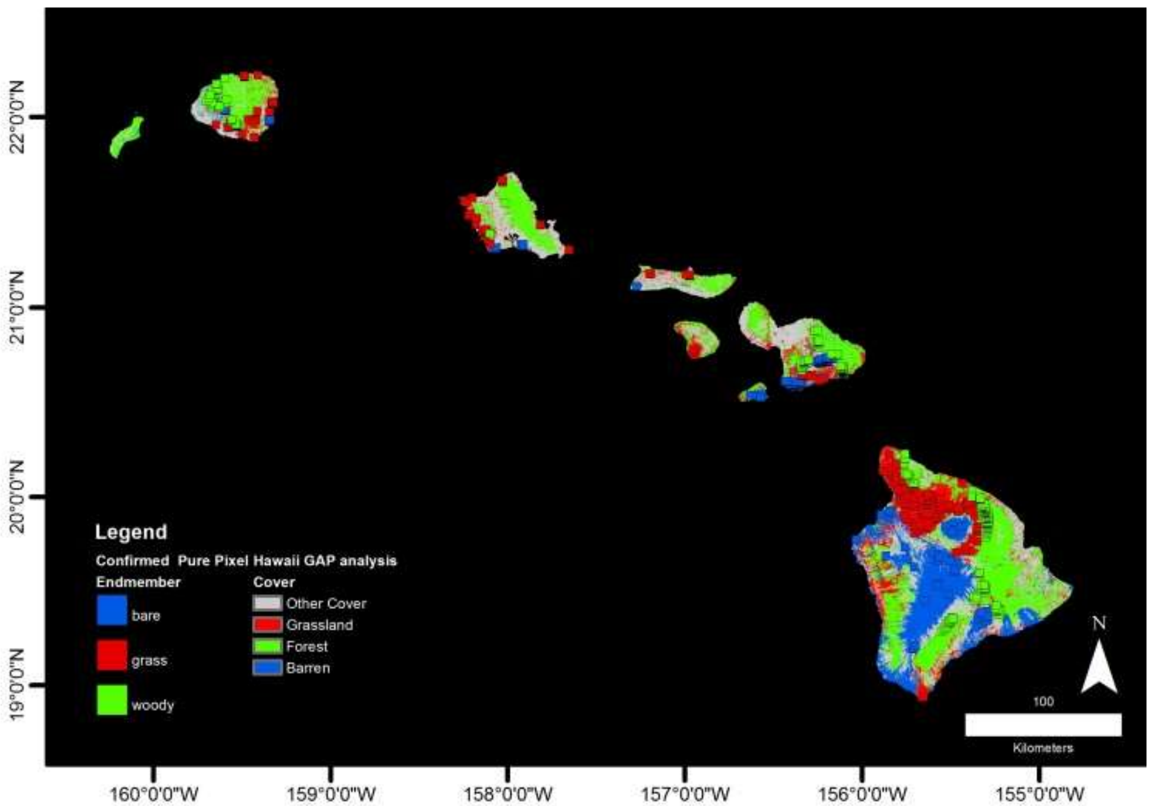

Figure 3: 2000 HI Gap "Cover" class and confirmed pure pixel locations statewide

Pre-Processing, Image Masking & Creation of Cloud-Free Statewide Images

To standardize LANDSAT 7 spectra and to reduce noise from clouds and shadows, the following preprocessing and masking steps were performed to derive statewide, cloud-free composite images for Hawaii. GEE houses a complete LANDSAT image collection that automatically runs the FMASK algorithm (Zhu et al. 2015) adding an additional band that identifies clouds, and cloud shadows.. However this dataset is only corrected to the top of atmosphere (TOA). At the time of publication no complete LANDSAT dataset existed that contained the FMASK cloud mask band with atmospherically corrected spectra. Using the image ID, the TOA FMASK collection was merged with the LANDSAT image collection where surface reflectance is corrected using the LEDAPS model

(Pons, et al. 2013). This allowed for composites and/or mosaics to be constructed from multiple images using only pixels that were cloud free and not shadowed by cloud.. Several methods and temporal groupings of composited, mosaicked imagery were used to create a time series of continuous statewide, multi-spectral (bands 1-5 & 7) images. This included 3-month seasonal, 6-month seasonal, and 12 month annual images, with intra-annual images utilizing a composite (mean or median) or quality mosaics method (selected pixel with highest value of grass and or woody cover) to construct an annual statewide sub-pixel fraction cover estimate using spectral unmixing (table 1). Validation data of cover (Wright, et. al 2002) will be used to determine the most robust temporal composite and annual unmixed mosaic method (table 1).

Automated Separation of “Green” and “Dry” Fine Vegetation

Due to the temporal variability in spectral signatures of herbaceous vegetation caused by phenological responses to rainfall (i.e., “greening” and “browning), an automated method was developed to bin mean spectra of confirmed pure pixel locations of grass/fine vegetation into “green” and “dry” respective endmembers. For each endmember confirmation of pure grass/fine vegetation pixels (see above), both date of Pictometry ™image and a binary assessment of “greenness condition” (green or dry) was recorded. Spectral bands 1-5 and 7 and LANDSAT image date from every available LANDSAT 7 image were sampled at the location of each grass / fine vegetation pure pixel. Using R software (Ihaka et.al 1996), the table of Pictometry ™observed grass / fine vegetation pure pixel “greenness condition” was merged into a single table with the LANDSAT 7 image date and spectral bands. An additional column was added that calculated the date difference in days from the LANDSAT 7 observation and Pictometry ™observation. This column was then used to subset all LANDAT image spectral observation to those that occurred within 8 days of the pure pixel Pictometry ™ “greenness condition” observation (max: n=74, see **table** 2). Several vegetation indices (VI) were calculated and a binomial general linearized model (GLM) was fit where a “green”=1 and “dry”=0 was a function of VI value. This process was iterated through a moving window of days from 0 to 8 +/-of included co-occurrence of observations (LANDSAT 7 and Pictometry ™ “greenness condition”).This resulted in nine GLM models per vegetation index. Overall, NDVI proved the “most robust” performing VI based on explained deviance of the model and models were averaged over all co-occurrence day bins to derive a threshold for NDVI (0.45477) to differentiate “green” from “dry” herbaceous vegetation (figure 4). This threshold was then used to construct “green” and “dry” image masks for use in spectral image sampling of respective “grass/fine vegetation”.

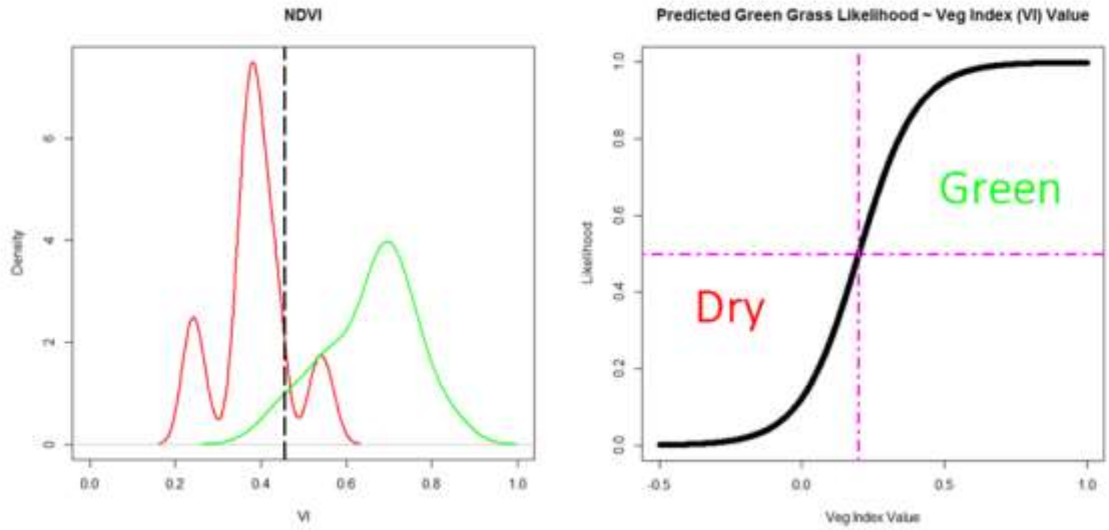

Figure 4: Density of "dry" and "green" observed pixels over NDVI value, dashed line is determined threshold. (L) Example of GLM binomial fit of Green vs Dry over NDVI value, pink horizontal line represents 0.5 likelihood and vertical pink line represents corresponding NDVI value. (R)

Creation of Statewide Annual Sub-pixel Fractional Cover Images

To produce annual sub-pixel fractional cover estimate for the three generalized cover types (woody, grass, and bare) for the entire extent of the main Hawaiian Islands, application of custom linear spectral unmixing coded workflow was undertaken in GEE. The objective was to create an annual continues coverage sub-pixel fractional coverage map from statewide cloud free image composites. This automated process was performed on all combinations of statewide cloud-free composite images described above (table 1). The work flow automated GEE code performed the following steps: (i) separating each composite image space into "dry" and "green" areas for herbaceous cover using a pre-calibrated NDVI threshold, (ii) extracting and calculating band (1-5 & 7) mean surface reflectance at pure pixel locations for each of the four endmember (forest/coarse vegetation, dry grass/fine vegetation, green grass/fine vegetation & bare earth) from each composite image, (iii) deriving mean spectral values of endmembers in a non-negative (using a non-negative least squares model), constrained to one (using a Lagrange multiplier method) linear spectral unmixing model applied on each temporally binned composite image, (vi) calculating the per pixel band values error between all mean endmember and band values (to calculate root mean square for error evaluation), (v) adding together fractional estimates of dry and green grass/fine vegetation endmembers to make a single all grass/fine vegetation fractional cover estimate and for intra annul unmixed image, , (vi) producing an annual fractional cover estimate by compositing (using mean or median) or quality mosaicking (using pixel with highest grass or woody pixel) . This workflow was applied on all temporally grouped composite images to create three early period (1999, 2000, 2001) annual sub-pixel fractional cover estimates for use in validation (see below).

Validation and Identification of Most Robust Image/Unmixing Method

To evaluate liner spectral unmixing performance across all temporally binned (12 month annual, 3-month seasonal and 6-month) composite/mosaic methods, validation of was performed using an early period (1999-2001) dataset of measured percent cover data from the USDA (Clinton et.al 2002). The "most robust" method(s) was determined by evaluating observed plot cover relationship to estimated annual unmixed value for all three covers both independently and combine. Ranking of methods was done by using root mean square error (RMSE) and R-squared of all cover types (grass, woody, bare) individually, as well as combination into all cover (table 1). The best method for producing annual fractional cover image was identified as having the highest R-squared and lowest RMSE when all covers were combined and compared to plot estimates (table 1).

The "best method", was applied to all years in study range (1999-2016, LANDSAT 7) to create an image collection of 17 annual sub-pixel estimates of the three broad cover types. An assessment of the spatial variability of this "most robust" method was performed by visually examining RMS images and looking for grouped high abnormally values, corresponding to image anomalies or poorly attributable land cover. Finally this "most robust" method was also checked and validated against a smaller dataset of late period (2016) (Zhu et.al 2016) cover plots. These plots were not used to determine best composite/unmix method selection as they only occurred on Hawaii Island, and had limited observations of high tree cover. However, the performance of the best method against these independent cover samples had to be considered "satisfactory", as defined above, for this method to be deemed suitable for examining change and cover dynamics statewide. After this final late period confirmation the best method was applied to all available 17 years of LANDSAT 7 imagery.

Quantifying Land-Cover Change

To identify pixels where change has occurred, as well as estimate rates of cover change during the study period, the GEE platform was used to run an ordinary least squares (OLS) linear regression for each pixel where fractional cover (converted to percent) was modeled as a function of time (year). This produced over 54,000,000 regression results (~18,000,000 pixels * 3 cover types) that were used derive a cover trend image with slope (representing % change per year) and intercept stored as bands for each cover type. Several regression statistics were used as significance thresholds to conservatively distinguish changing and stable pixels. This included: (i) calculating the 99.9% confidence interval (CI) of the slope and eliminating all pixels where none or only one of the three covers annual rate of change (ie: slope +/-) CI fell below 1% or above -1% per year (signifying at least two covers are significantly changing at an absolute rate of >1% per year), and (ii) excluding pixels where a single cover regression produced an R-squared less than 0.5 excluding pixels that had poor fits over the study period. The remaining "real change" pixels were used assess the area and rate of change. Model predictions from the regressions were used to estimate actual per pixel cover at the start and end dates of the image collections (1999 and 2016) to calculate total net change in cover over the 17 year sample period. This was done by constructing the modeled linear relationships for 1999 and 2016 cover estimates within the "real change" pixels space. All other pixels where change was not detected, the 17 year mean percent cover were applied. Final aggregated area (ha) estimates of cover loss or gain were calculated by multiplying the fractional cover of a space by the area of a 30 x 30 meter pixel (0.09 ha).

Spatial "Causes" of Change

To attribute real change pixels to potential land use causes, an additional statewide spatial layer of past and current agricultural land use, planning intended use, county zoning, intensive conservation / restoration actions and known burnt areas spatial was created in ArcGIS 10.3.1(figure 5) . Each "spatial cause" is defined with its origin and attributes explained in table 3. The combinations of these multiple datasets relied upon creating a ordering where each layer of higher rank trumped all layers below it. For example, all current agricultural land use (Perroy et.al 2016) took precedence over any lower order space such as past agricultural land use (ALUM 1980). Creation of this cause layer was constrained to open data source of existing data sets. Characteristics of land cover change were attributed to each "cause" space both statewide and for each island. Measurements of change pixels included: per cause total area of change, mean rates of change (as mean percent cover change per year), and final net and gross cover outcomes (by applying per change pixel linear fit to 1999 and 2016 years). Change characteristics were not calculated within currently cultivated annual agriculture, as agricultural crops as a landcover type is not parameterized in the unmixing model and as such detected changes in active cultivated land represent on going land use of agriculture and not land cover change. However several other forms of agriculture such as orchard trees and forestry are included when tallying land cover change, because their landcover outcomes (ie: increasing tree cover) fit within the unmixing model. Finally we recognize that not all land use history is represented in these data, and acknowledge that several land uses/events might have occurred in overlapping space and time, however this dataset represents an attempt at broadly cataloging known land use and fire history statewide.

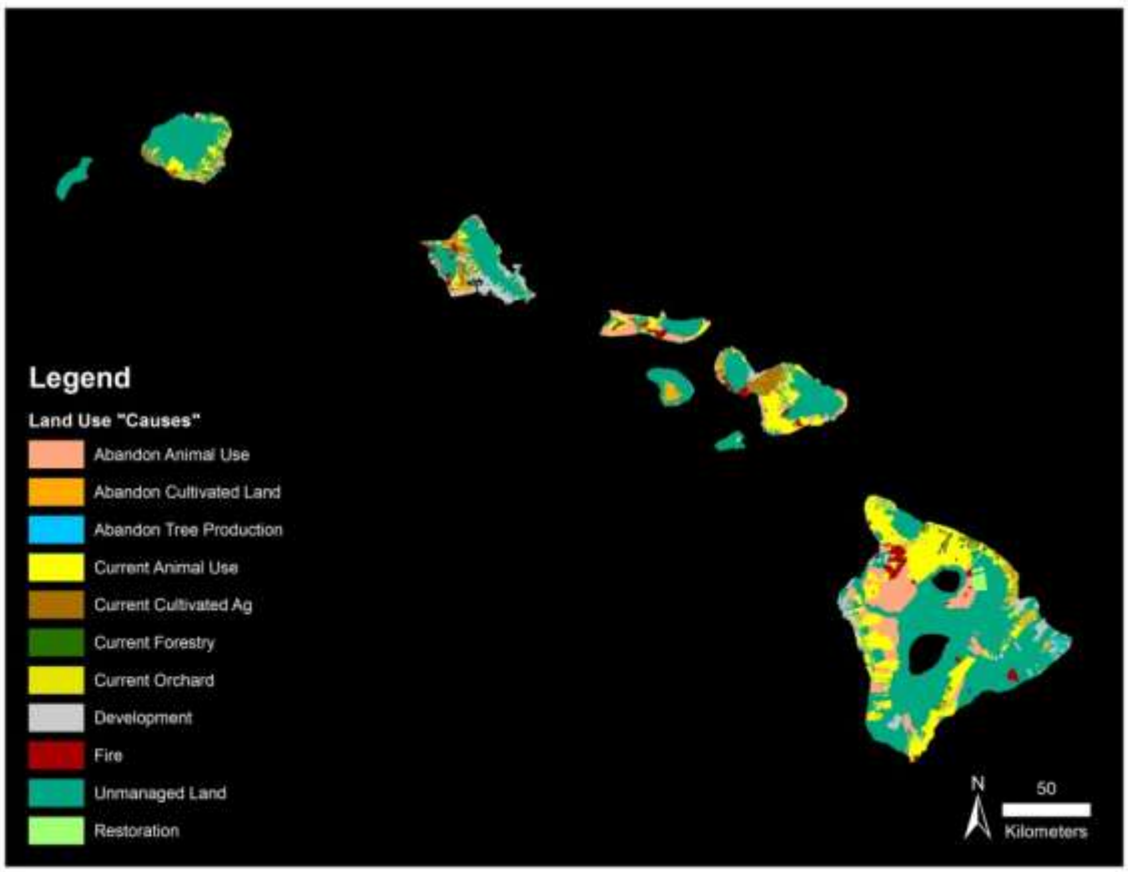

Figure 5: Statewide spatially defined land use "causes" constructed from multiple sources delineating current and past land use as well as disturbance (fire)

Results:

Unmixing Method Validation

Of all composite / mosaic unmix methods from the 17 workflows tested, ten produced "satisfactory" validation results of RMSE<25 and R-squared of > 0.6 (table 4). All these acceptable methods relied upon producing a sub-annual cloud-free composite image at a 6-month semi-annual time-step (n=4) or quarterly at a 3-month time-step (n=6). The top four methods all employed a quality mosaic, where the seasonal image pixel (including all three fractional covers) with the highest observed grass value was used mosaic the annual fraction cover image. The best composite/mosaic unmixing method with the lowest all cover RMSE and highest overall R-squared overall utilized a 3-month cloud-free mean composite image, that was then unmixed, and annual fractional cover was assembled from a quality mosaic of the quarterly unmixed images, of the highest fractional cover of grass pixel. Validation, of the best composite / fractional cover mosaic method using USDA cover data (Wright et.al 2002)produced RMSE and R-squared of 19.61 and 0.72 respectively (table 1, figure 6). An additional test using a spatially limited set of late period (2016, n=17, Zhu et.al, figure 7) cover plots validated against all cover with "satisfactory" findings producing an RMSE of 22.58 and an R-squared value of 0.65, respectively. RMS images from this method were visually examined and we found no major discrepancies. However, we observed higher RMS in known bare lava flows and summit areas, with generally the lowest RMS values being observed in areas of known grass cover and continuous forest.

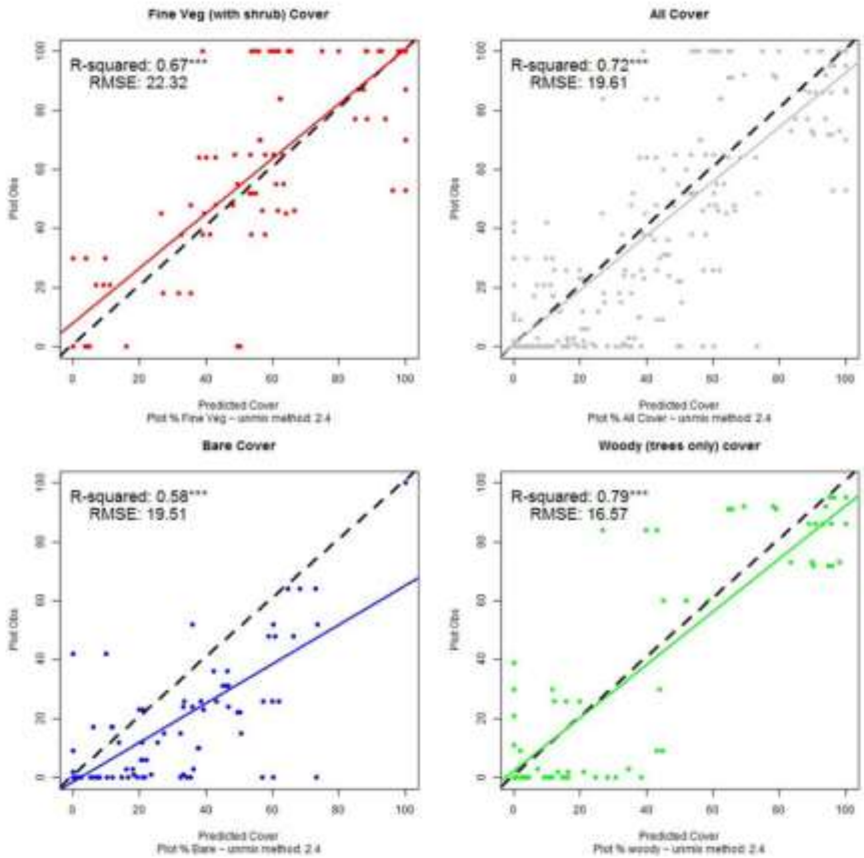

Figure 6: Validation plots for all three covers and combine all cover, of "most robust " unmixing method over USDA cover data for 1999, 2000, 2001. Dashed line is 1:1 line with colored solid line showing the liniar line of the relationship.

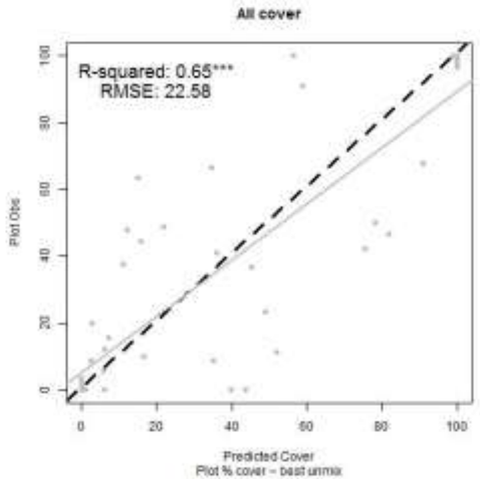

Figure 7: 2016 Validation plot for all combine cover, of "best" unmixing method over 2016 plot data. Dashed line is 1:1 line with colored solid line showing the liniar line of the relationship.

Quantifying Statewide Change

Our analysis estimates approximately 102,910 ha or 6.4% of the total landmass (as calculated by count change pixels/count total pixels [1,143,442/18,000,842]) of the main Hawaiian Islands has undergone cover change over the past 18 years. Change was detected on all islands (figure 8 & 9) with the largest area of change occurring on Hawaii Island (58844.6 ha, figure 8 & 9). However island proportional area calculations showed Maui and Molokai with the largest percent of area changing at 8.7% and 8% respectively (figure 8).

In 1999, we estimate 677,448.9 ha of grass/fine vegetation cover, 449,420.2 ha of woody/coarse vegetation cover, and 453,190.1 ha of bare cover across the study area. By 2016, we estimate that grass and fine vegetation cover had declined 0.96% statewide to 670,884.5 ha, woody/coarse vegetation increased 1.67% statewide to 456,958.4 ha, and bare substrate remained relatively stable statewide (-0.21% change) at 452,216.2 ha (table 4). Thus, from 1999 to 2016, Hawaii gained 7,538.2 ha of coarse vegetation/ woody cover and lost 6,564.4 ha of grass/fine vegetation and 973.9 ha bare earth (figure 10 and table 4). Five of the eight Hawaiian Islands had net gains in coarse veg/ woody cover. Woody cover increases on Hawaii Island contributed the most (85%)to the overall statewide net gain (table 4). Half of the eight islands studied had net increases of grass with Maui contributing most amount of grass cover gain at 1144 ha (see table 4).

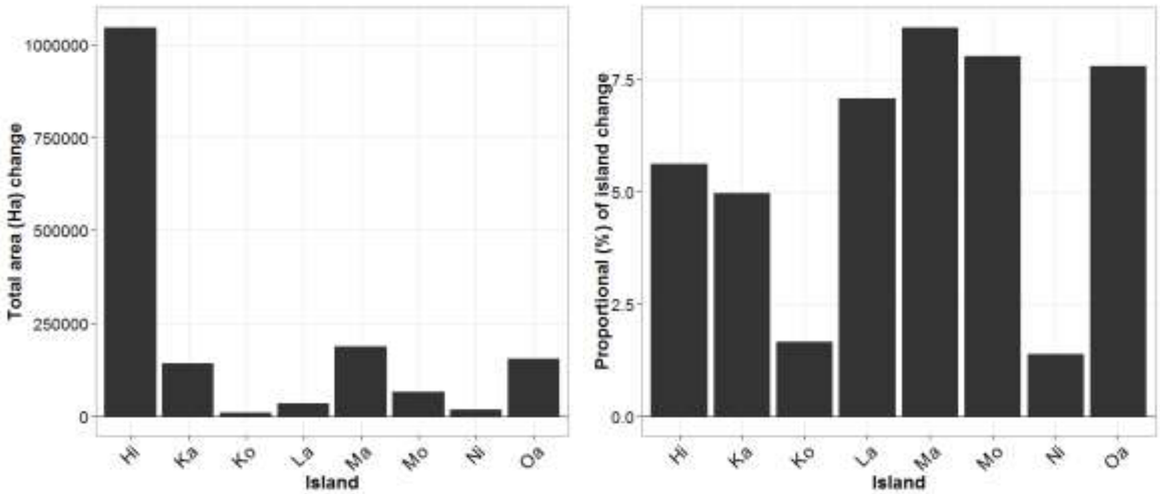

Figure 8: Total area (ha) of change per island (above) and % percentage of total area changing per island (below)

Attributing Change to Spatial Land Use and Burned Area "Causes"

Change occurred in all spatially defined causes, with the largest amount of area of change, z Ha, occurring within natural/unmanaged areas. Land use "causes" with the largest amount of area changing were natural/unmanaged areas , current animal use and abandoned animal use with 38136.8 ha, 19054.1 ha, and 13639.7 ha of changing land respectively (see figure 11). The "cause" with the largest change as of proportional area of spatial "cause" were current forestry, abandoned cultivated land and development with 43.4%, 18.3%, and 13% respectively (see figure 11). The largest area (ha) of net gains were increases in woody cover in current animal use, current forestry, abandoned animal use and unmanaged areas, resulting in 2608.8 ha, 2534.7 ha,1642.9 ha, and 1449.7 ha of net woody cover increase respectively (figure 9). Current animal use occurred on five islands, and four of these islands had net gains in the extent of woody vegetation (ha) within this cause category , with the largest per island net increase occurring on Hawaii island where woody cover increased 2,121.1 ha (see table 4).

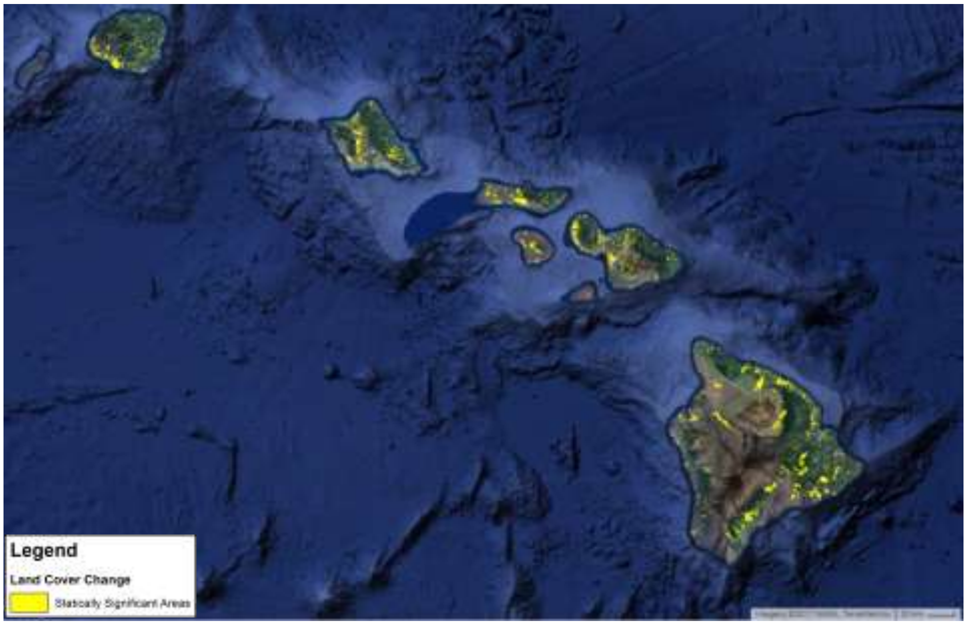

Figure 9: Statewide map of all statically significant "real change" pixels (yellow)

Highest mean rates of cover gain were measured in woody cover increasing at 3.7% per year within current forestry areas and 2.1% per year within restoration efforts. The greatest negative rates of cover loss were mirrored by those same causes with the fastest gains, with grass cover reducing within forestry areas and restoration efforts at -3.5% and -2.2% per year respectively (see figure 12).

Current forestry was delineated on four islands, with three islands having net woody area (ha) gains, with the largest by far per island net increase occurring on Hawaii island where woody cover increased 2,512.9 ha (see table 4). All five islands where abandon animal use occurred showed net gains woody area (ha), with the largest per island net increase occurring on Hawaii island where woody cover increased 1,236.2 ha (see table 4). Woody increase in natural / unmanaged areas occurred on seven of all eight islands, with the largest net gain of 568.8 ha occurring on Oahu.

The largest areas of net grass area (ha) increase occurred in abandon cultivated land (1196 ha), development (1004 ha), and where fires have occurred (403.8 ha; see figure 12). The single largest net gain of grass occurred on Maui within abandon agriculture and resulted in a net grass cover gain of 1431 ha (see table 4). The largest net bare area increase of 1907 ha occurred in unmanaged/natural areas on Hawaii Island (see table 4).

Discussion

Statewide Vegetation and Cover Transitions

The linear spectral unmixing results and regression analyses indicate a substantial portion (6.4%) of land cover in Hawaii in flux. This is not surprising as over the past decades large areas of the state have undergone land use change such as agricultural abandonment (Perroy et.al 2016) and been altered by invasive species (Asner et.al 2008). While many abandoned agricultural lands lead to overall net increases in grass/fine vegetation cover, for example on Maui, this grass gain was offset statewide by net gains of woody cover, primarily occurring in natural unmanaged areas, abandoned animal usage and forestry operations. This trend suggests that woody expansion is driven by both active afforestation efforts and passive woody encroachment in underutilized pastures and across unmanaged lands. These overall net gains of woody cover across the state are aligned with other forest transitions pathways observed at several locations around the world in regards to land use land cover change outcomes (Meyfroidt et.al 2011). Several potential pathways to net forest gains (Meyfroidt et.al 2011), and as our findings suggest several of these forest transitions pathways are present in areas across Hawaii (figure 13) and presented below.

Woody expansion in Hawaii is occurring in current and abandoned agricultural lands we suspect this is largely in part due to statewide waning agricultural land use. The unmixing results clearly show how abandon agricultural land are associated with increased forest and woody cover. This naturalization of woody species in abandoned lands is similar to patterns to those agricultural abandonment drivers observed in Puerto Rico (Rudel et.al 2000). As the US and Hawaii became more affluent, land prices, production and labor cost have increased; meanwhile increasing globalization has allowed for the importation of cheaper agricultural products (Suryanata 2002, Perroy et.al 2016). Another forest transition pathway illustrated by our analysis is that of agricultural conversion to commercial forestry. This pathway is similar to global forestry driven transitions observed in Argentine Atlantic forests (Izquierdo et.al 2008). Restoration and rehabilitation of degraded or deforested areas also emerged as reason for the forest transition in Hawaii. Woody cover increases in restoration and conservation areas showed the second highest rate of increase, albeit at small scales, after plantation forestry. These results indicate that conservation and restoration efforts where public and private partnerships work together to rehabilitate landscapes (Meyfroidt et.al 2011) are resulting in forest expansion. It is important to distinguish these efforts from plantation forestry because restoration results in very different ecological outcomes such as increased species diversity when compared to forestry (McNeely 2004).

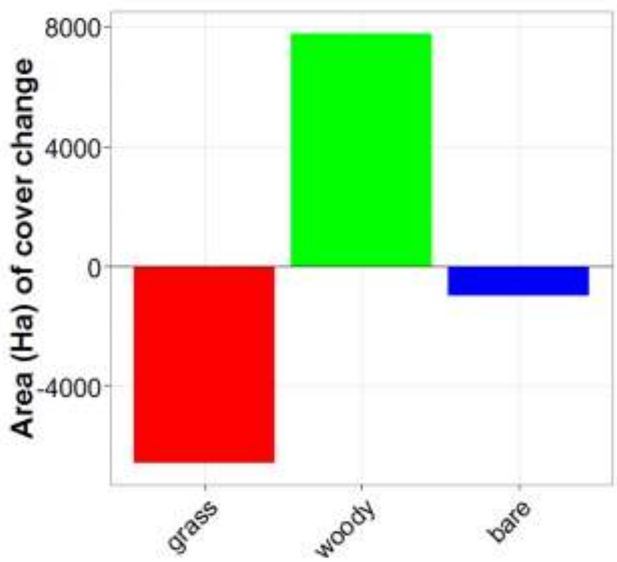

Figure 10: State wide net cover outcomes in area of cover ha

The largest extent of change occurred in natural unmanaged areas (figure 11) across Hawaii, substantially contributing to the net gain of woody cover statewide (figure 10, table 4). These areas are complex in terms of defining causes because multiple processes may be affecting land cover change. Initial and ongoing native forest declines starting with human arrival have been reinforced through both feral and domestic ungulate introductions and widespread establishment beginning as early as 1793 (Cuddihy 1990). It is known that introduced ungulates in Hawaii consume young germinating tree and woody seedlings and retard growth of maturing plants, clearing space for non-native plant species establishment (Blackmore and Vitousek 2000). Long-term and ongoing degradation of native forest from non-native ungulates (Scowcroft et.al 1983) are also coupled with the widespread establishment of fast growing, invasive woody plants which have resulted in significant compositional change at the site level (Leary et.al 2006, Hughes et.al 2005, Vitousek et.al 1989). Invasive plant establishment has been documented globally (Kueffer et.al, 2010) and recorded on many islands with similar land use patterns (Strasberg et.al 2005). Based on largely anecdotal information from statewide weed control efforts, non-native woody species may be a key factor underlying the large scale woody cover expansion of observed in unmanaged areas across the state. For example, regional vegetation experts have confirmed invasive woody expansion at several locations of detected woody increase (figure 13), however, the complete details on invasive species extent and its total contribution to these land cover outcomes calculated in this study merits further investigation. If increasing woody cover is in fact due to invasive species expansion, this has important implications for ecosystem functioning and ecosystem service provisioning, as these species are known to reduce ground water recharge, surface water quality as well as native biodiversity (Meyer et.al 1996,. Funk et.al 2007).

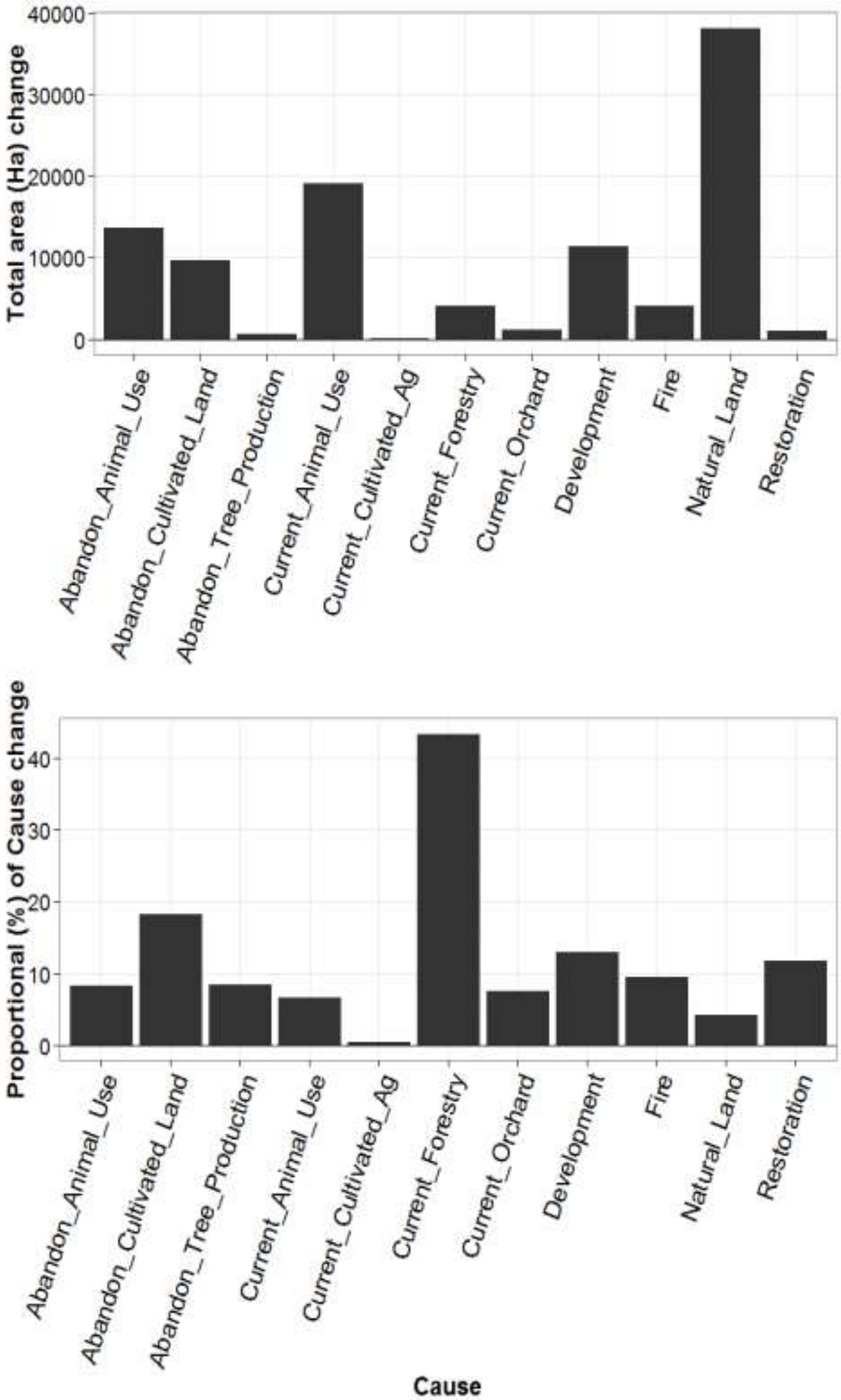

Figure 11: Total area (ha) of change per land use cause (top) and % percentage of total area changing per cause (bottom)

Despite the statewide net loss of grass cover, several causes and spatial patterns contributed local sizeable areas of grass expansion. In line with anecdotal observation of invasive species expansion, several locations showed grass cover increases over former bare land areas (e.g., north Kona and Saddle Road regions on Hawaii island). Grass cover also increased substantially in abandoned agricultural lands, a commonly observed land cover pathway as weedy herbaceous plants are very quick to colonize (Cramer et.al 2008).. Maui was one of two islands with net grass gains detected with the majority of grass increase occurring in recently abandoned sugar cane and pineapple plantations (Perroy 2016). Other problems have been linked to the abandonment of agriculture lands, including soil erosion, reduced landscape heterogeneity and increased fire risk (Benayas et.al 2007, Cramer et.al 2008). In Hawaii, non-native fire adapted weeds are widespread and create a self-facilitating relationship with fire occurrence (D'Antonio et.al 1992). This combination of agricultural abandonment and grassland expansion is of particular concern in Hawaii where fire occurs year round, widespread and associated with adjacent human development (Trauernicht, et.al 2015). This outcome is directly supported by the unmixing results that indicated net grassland and bare area expansion in burned areas (figure 12). Documenting these outcomes are critical to understanding the impacts of land use change in Hawaii given he continued trajectory of agricultural abandonment, most recently illustrated with the closing of the last large scale sugar producer on Maui.

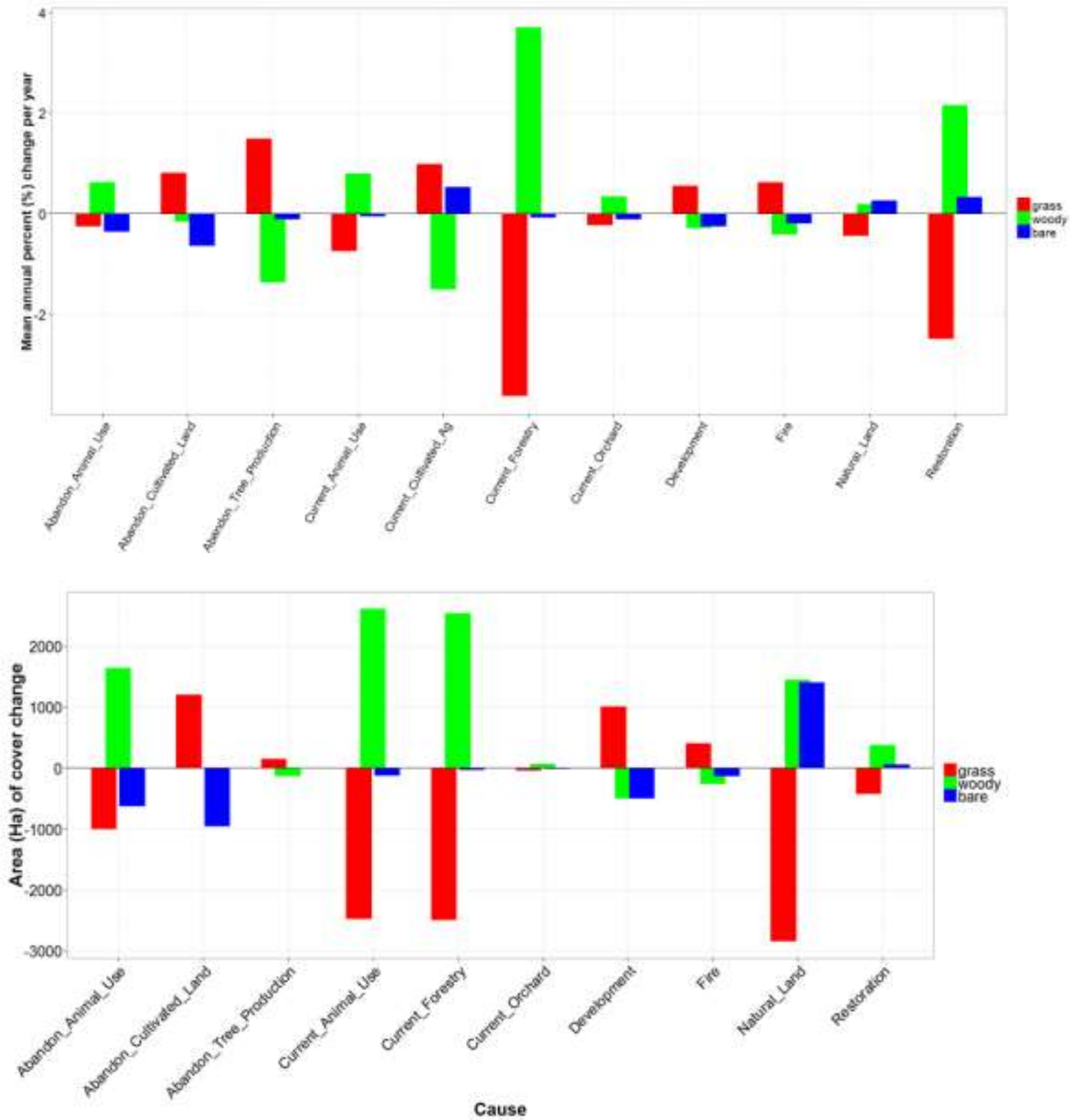

Figure 12: Mean per cover rate of change by cause (top). Total per cover net area of change by cause (bottom)

Unmixing Performance, Limitations and Potential Applications

The overall performance, of the unmixing of (1) composite images, (2) across various image scenes, produced good repeatable indices of the dynamics of the three land covers studied. While accuracy (in the form of R-squared), was very good, the variation in the measurements precision (in the form of RMSE) means careful application of cover data produced should be practiced. For this study the application of the OLS regression enriched change detection as well as providing statistical means for producing change pixel cover estimates. Simple difference calculations of any given years will undoubtable produce poor and potentially abnormal results. Future uses of this cover dataset should incorporate statistical methods that allow or account for variation in measurements and leverage overall data trends. Finally, we admit and stress that the data produced does not reflect any measurement or estimate of vegetation quality condition, or ecological composition. As such we stress that data should not haphazardly be used for this purpose without, (i) on the ground or expert confirmation of change occurrence and ecological composition, and (ii) clearly delineation spatial extents of these ecological compositions.

Several (n=10) spectral compositing and fractional cover mosaicking methods over time and space produced low (>20) RMSE and acceptable R-squared values; suggesting that this approach is a reasonable compromise to achieve a larger more complete image for endmember sampling and unmixing across image scenes in highly cloudy areas. However it was observed, that when the temporal bin is increased over seasons (and potentially vegetation phonologies) overall accuracy and precision is reduced (table 1). As such all of the best composite methods applied a 3 month composite, likely owing to the utility of having composite pixel spectral be temporally grouped into an ecologically appropriate time-step (ie: 3 month hydrological seasons). This increased performance is also echoed by the use of the highest 3-month grass estimate as the best means of mosaicking unmixing data together to build a statewide annual estimate; we suspect that cover might be easier to unmix during dry periods when grass and tree cover are more spectrally dis-similar.

Due to the continuous nature of the cover data produced and the uninterrupted documentation of these landcover observations, several other potential applications for this product could include: (i) impacts of drought on annual and intra annual woody cover, statewide assessment of extent and rates of change on various methods of native forest restoration, and (iii) analysis on the impact climatic conditions and management on invasive species spread.

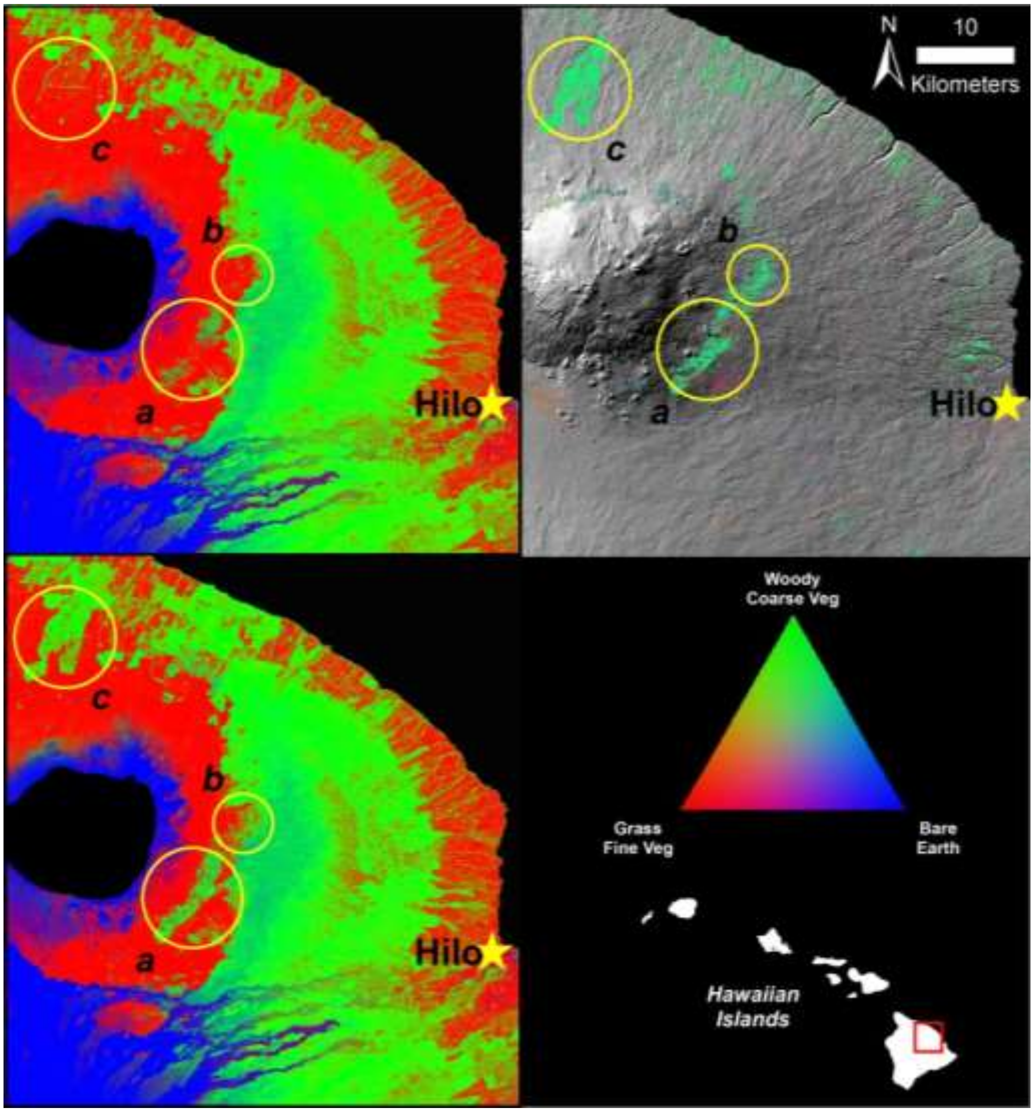

Figure 13: NE Hawaii island - 1999 modeled fractional land cover (UL), 2016 modeled fractional land cover (LL), hill shade with "real change" pixels and slope (cover % per year) as color brightness. Yellow circles indicate various areas of different woody transitional pathways: (a) invasive woody gorse in abandon pasture land, (b) Native Koa restoration in Hakalau NWR, (c) commercial forestry in past agricultural lands

Conclusions

Overall spectral linear unmixing of composite LANDSAT 7 images provided a very effective means of creating annual mosaics of sub-pixel fraction land cover. Furthermore the continuous nature of this data and its repeated annual measurements allowed for successful use of statistical trend analysis to highlight areas of landcover change, and quantify rates of change. The land cover product produced from this analysis as well as the mythology applied should facilitate for numerous local case studies of land cover change land use dynamics as well as contribute potential additional approaches for the land systems science as a whole.

Findings indicated that approximately 6.4% of the state is changing, owing to widespread past and ongoing agricultural land use changes (Perroy et.al 2016). Given the more recent closures of the last large-scale sugar producer, HCNS, and the observed rapid increase in grass cover measured in past cultivated lands, we expect several areas of grass cover expand. With more grassland expansion, especially occurring adjacent to housing, we would expect fire risk to increase in these areas.

Despite these local gains in grass cover, total statewide net change resulted in a gain in woody cover. Largest areas of change are occurring in unmanaged areas, current and past pastoral land, current forestry and abandon cultivated land. These findings suggest that Hawaii is going through a forest transition. This is primarily driven by tropical agricultural abandonment including large swaths of neglected and deserted pastoral land, but also influenced by establishment of forestry production on past agricultural land and potential for native species restoration and afforestation. Owing to the largest area of change occurred in places where no direct human land use occurs, resulted in a net woody cover gain, and aggressive invasive woody species are widespread, a novel, invasive species expansion, forest transition scenario is proposed for Hawaii and other oceanic tropical islands. Surprising, a large amount of changes was detected in 'unmanaged areas'. Based on our understanding of invasion and management in these areas (Scowcroft et.al 1983, Blackmore and Vitousek 2000, Hughes et.al 2005) a novel non-native forest transition dominated by aggressive invasive woody species is likely. To fully investigate these and other impacts will require more detailed field assessments and local expert knowledge of change and cover composition. This work would vastly improve the understanding of the direct land cover impacts from land use changes, and provide researchers, managers and decision makers a means to evaluate landscape scale consequences of land use and management choices.

Tables

Table 1: Composite unmxing methods with ranked by R squared and RMSE

Temporal Bin	*Cloud-free Image Creation Method*	*Annual Fractional Estimate*	*RMSE*	*R-Squared*
Seasonal 3-month	Spectral Mean Composite	Annual quality mosaic (max grass estimate)	*19.61*	0.72
Seasonal 3-month	Spectral Median Composite	Annual quality mosaic (max grass estimate)	*19.85*	0.71
Seasonal 6-month	Spectral Mean Composite	Annual quality mosaic (max grass estimate)	*21.33*	0.67
Seasonal 6-month	Spectral Median Composite	Annual quality mosaic (max grass estimate)	*22.11*	0.64
Seasonal 3-month	Spectral Mean Composite	Annual Fractional Median	*22.56*	0.62
Seasonal 3-month	Spectral Median Composite	Annual Fractional Mean	*22.59*	0.62
Seasonal 3-month	Spectral Mean Composite	Annual Fractional Mean	*22.63*	0.62
Seasonal 3-month	Spectral Median Composite	Annual Fractional Median	*22.69*	0.62
Seasonal 6-month	Spectral Mean Composite	Annual Fractional Mean	*22.81*	0.61
Seasonal 6-month	Spectral Mean Composite	Annual Fractional Median	*22.81*	0.61
Seasonal 6-month	Spectral Median Composite	Annual Fractional Median	*23.47*	0.59
Annual 12-month	Spectral Median Composite	Annual Composite Image Unmixed	*23.51*	0.59
Seasonal 6-month	Spectral Median Composite	Annual Fractional Mean	*23.85*	0.58
Annual 12-month	Spectral Mean Composite	Annual Composite Image Unmixed	*23.92*	0.58
Seasonal 6-month	Spectral Mean Composite	Annual quality mosaic (max woody estimate)	25.21	0.54
Seasonal 3-month	Spectral Median Composite	Annual quality mosaic (max woody estimate)	26.27	0.50
Seasonal 3-month	Spectral Mean Composite	Annual quality mosaic (max woody estimate)	26.80	0.48

Table 2: NDVI green/dry grass GLM results for various moving window of co-observation

Vegetation Index	Day Window	Pixel Count	Explained Deviance	Vi Split Value
NDVI	0	7	100.0%	0.42790
NDVI	1	11	100.0%	0.42782
NDVI	2	24	100.0%	0.42784
NDVI	3	21	60.8%	0.45322
NDVI	4	37	65.7%	0.45477
NDVI	5	50	65.9%	0.46860
NDVI	6	36	61.2%	0.47618
NDVI	7	65	65.5%	0.48190
NDVI	8	74	66.6%	0.47470
Mean	**4**	**36**	**76.2%**	**0.45477**

Table 3: Description and hierarchy of spatial land use "causes" with data source and provenance

Cause	Hierarchical Rank	Data Source	GIS Attributes	Data Description
Fire	1	USGS Monitoring Trends and Burn Severity (MTBS) http://www.mtbs.gov/products.html	All Data	USGS Monitoring Trends and Burn Severity (MTBS) Remotely sensed burned area boundary as detected from postfire imagery areas across Hawaii from 2001-2011
Development	2	SLUD - Office of Planning - Hawaii Statewide GIS Program planning.hawaii.gov/gis/	LUDCODE - R Rural Land Use & U Urban Land Use	State Land Use District Boundaries (SLUD)
Development	2	Zoning (Hawaii County) - Office of Planning - Hawaii Statewide GIS Program planning.hawaii.gov/gis/	zone - A1a & A3a	Hawaii County Zoning as of November, 2015. Source: County of Hawaii, Planning Dept.
Restoration	3	Hand Digitized	N/A	Expert Knowledge of location and extent of longterm (10+) years of restoration work.
Current Animal Use	4	Ag Baseline 2015 - Office of Planning - Hawaii Statewide GIS Program planning.hawaii.gov/gis/	CropCatego - Dairy, & Pasture	2015 Hawaii Statewide Agricultural Land Use Baseline layer a snapshot of contemporary commercial agricultural land use activity in Hawaii.
Current Cultivated Ag	4	Ag Baseline 2015 - Office of Planning - Hawaii Statewide GIS Program planning.hawaii.gov/gis/	CropCatego - Aquaculture, Diversified Crops , Flowers/Foliage/Landscape, Pineapple, Seed Production, Sugar, & Taro	2016 Hawaii Statewide Agricultural Land Use Baseline layer a snapshot of contemporary commercial agricultural land use activity in Hawaii.
Current Forestry	4	Ag Baseline 2015 - Office of Planning - Hawaii Statewide GIS Program planning.hawaii.gov/gis/	CropCatego - Commercial Forestry	2017 Hawaii Statewide Agricultural Land Use Baseline layer a snapshot of contemporary commercial agricultural land use activity in Hawaii.
Current Orchard	4	Ag Baseline 2015 - Office of Planning - Hawaii Statewide GIS Program planning.hawaii.gov/gis/	CropCatego - Banana,Coffee,Macadamia,Papaya, & Tropical Fruits	2018 Hawaii Statewide Agricultural Land Use Baseline layer a snapshot of contemporary commercial agricultural land use activity in Hawaii.
Abandon Animal Use	5	ALUM - Office of Planning - Hawaii Statewide GIS Program planning.hawaii.gov/gis/	COMMODITY - A-1 Grazing, A-2 Dairy, A-3 Hog, A-4 Poultry	State Department of Agriculture 1978-80 and the US Soil Conservation Service Hawaiian Agricultural Land Use Maps (ALUM)
Abandon Cultivated Land	5	ALUM - Office of Planning - Hawaii Statewide GIS Program planning.hawaii.gov/gis/	COMMODITY - F FIELD CROPS, F-1 Vegetables, F-2 Flowers, F-3 Foliage, F-4 Forage, P Pineapple, Q Aquaculture, S Sugarcane	State Department of Agriculture 1978-80 and the US Soil Conservation Service Hawaiian Agricultural Land Use Maps (ALUM)
Abandon Tree Production	5	ALUM - Office of Planning - Hawaii Statewide GIS Program planning.hawaii.gov/gis/	COMMODITY - O-1 Banana, O-2 Papaya, O-3 Macadamia, O-4 Avocado, O-5 Coffee, O-6 Guava, O-7 Other	State Department of Agriculture 1978-80 and the US Soil Conservation Service Hawaiian Agricultural Land Use Maps (ALUM)
Unmanaged/Natural Areas	6	SLUD - Office of Planning - Hawaii Statewide GIS Program planning.hawaii.gov/gis/	LUDCODE - A Agricultural Land Use & C Conservation Land Use	State Land Use District Boundaries (SLUD)

Table 4: All "cause" islands and statewide 1999 and 2016 gross and net cover outcomes (*cover gains in green, cover losses in red*)

Cause	Island	1999 Ha Grass	1999 Ha Woody	1999 Ha Bare	2016 Ha Grass	2016 Ha Woody	2016 Ha Bare	Grass Net Ha	Woody Net Ha	Bare Net Ha
Abandon_Animal_Use	Hi	56,337.4	19,433.2	46,942.3	55,617.6	20,669.5	46,425.9	-719.8	1,236.2	-516.4
Abandon_Cultivated_Land	Hi	11,708.4	4,102.1	337.9	11,125.4	4,738.1	284.9	-582.9	636.0	-53.0
Abandon_Tree_Production	Hi	3,684.0	1,976.7	149.4	3,736.7	1,936.3	137.2	52.6	-40.4	-12.2
Current_Animal_Use	Hi	151,414.7	38,401.4	21,389.8	149,255.5	40,522.5	21,427.8	-2,159.2	2,121.1	38.1
Current_Forestry	Hi	4,852.7	3,591.2	74.3	2,377.8	6,104.0	36.3	-2,474.8	2,512.9	-38.0
Current_Orchard	Hi	7,765.7	5,131.6	289.2	7,722.2	5,189.2	275.2	-43.5	57.5	-14.0
Development	Hi	17,017.1	9,733.2	10,736.3	17,859.3	9,168.9	10,458.3	842.2	-564.3	-278.0
Fire	Hi	17,401.8	1,804.0	4,177.6	17,369.4	1,559.5	4,454.4	-32.4	-244.5	276.8
Natural_Land	Hi	100,901.0	169,641.6	273,607.7	98,656.0	169,979.3	275,515.1	-2,245.0	337.7	1,907.4
Restoration	Hi	1,718.2	4,979.9	1,921.5	1,283.1	5,348.9	1,987.5	-435.1	369.0	66.0
	Island Ha Totals	***372,801.0***	***258,795.0***	***359,626.0***	***365,003.0***	***265,216.2***	***361,002.8***	***-7,798.0***	***6,421.2***	***1,376.7***

Cause	Island	1999 Ha Grass	1999 Ha Woody	1999 Ha Bare	2016 Ha Grass	2016 Ha Woody	2016 Ha Bare	Grass Net Ha	Woody Net Ha	Bare Net Ha
Abandon_Animal_Use	Ma	7,458.9	4,093.6	2,735.9	7,413.5	4,257.3	2,617.7	-45.4	163.7	-118.2
Abandon_Cultivated_Land	Ma	4,913.8	2,664.5	2,271.2	6,344.8	1,817.3	1,687.4	1,431.0	-847.2	-583.9
Abandon_Tree_Production	Ma	455.4	333.6	46.7	554.3	232.6	48.9	98.9	-101.0	2.2
Current_Animal_Use	Ma	31,572.3	6,578.1	4,161.6	31,221.8	6,757.4	4,332.6	-350.5	179.3	171.0
Current_Forestry	Ma	11.6	1.8	0.0	11.8	1.7	0.0	0.2	-0.2	0.0
Current_Orchard	Ma	167.5	148.8	21.7	181.5	135.9	20.6	14.0	-12.9	-1.1
Development	Ma	5,072.2	1,007.6	1,716.1	4,929.2	1,069.5	1,797.2	-143.0	61.9	81.1
Fire	Ma	4,613.7	784.9	1,722.6	4,783.2	807.0	1,531.0	169.6	22.1	-191.7
Natural_Land	Ma	30,525.8	40,957.0	17,470.9	30,498.6	41,132.6	17,322.4	-27.2	175.7	-148.5
Restoration	Ma	28.6	1.3	0.2	25.0	4.5	0.6	-3.6	3.2	0.4
	Island Ha Totals	***84,819.8***	***56,571.2***	***30,146.9***	***85,963.7***	***56,215.6***	***29,358.3***	***1,144.0***	***-355.6***	***-788.6***

Cause	Island	1999 Ha Grass	1999 Ha Woody	1999 Ha Bare	2016 Ha Grass	2016 Ha Woody	2016 Ha Bare	Grass Net Ha	Woody Net Ha	Bare Net Ha
Natural_Land	Ko	6,089.0	353.9	4,623.8	6,103.9	356.5	4,606.2	14.9	2.6	-17.6
Restoration	Ko	255.7	14.6	214.6	260.9	17.5	206.5	5.2	2.9	-8.1
	Island Ha Totals	***6,344.6***	***368.5***	***4,838.3***	***6,364.8***	***374.0***	***4,812.7***	***20.2***	***5.5***	***-25.6***

Cause	Island	1999 Ha Grass	1999 Ha Woody	1999 Ha Bare	2016 Ha Grass	2016 Ha Woody	2016 Ha Bare	Grass Net Ha	Woody Net Ha	Bare Net Ha
Abandon_Cultivated_Land	La	5,345.2	893.3	575.5	5,019.9	1,211.1	583.0	-325.3	317.8	7.6
Development	La	659.3	426.4	605.9	666.5	441.0	584.0	7.2	14.6	-21.8
Natural_Land	La	13,450.1	3,952.2	10,604.0	13,450.8	4,136.6	10,419.0	0.7	184.3	-185.1
	Island Ha Totals	***19,454.6***	***5,271.9***	***11,785.4***	***19,137.2***	***5,788.7***	***11,586.0***	***-317.4***	***516.8***	***-199.4***

Cause	Island	1999 Ha Grass	1999 Ha Woody	1999 Ha Bare	2016 Ha Grass	2016 Ha Woody	2016 Ha Bare	Grass Net Ha	Woody Net Ha	Bare Net Ha
Abandon_Animal_Use	Mo	13,009.8	3,602.9	5,308.5	12,812.1	3,807.5	5,301.6	-197.7	204.6	-7.0
Abandon_Cultivated_Land	Mo	292.3	63.9	69.2	299.2	70.0	56.3	6.9	6.1	-13.0
Abandon_Tree_Production	Mo	9.9	7.0	1.7	10.3	6.6	1.8	0.4	-0.5	0.1
Current_Animal_Use	Mo	8,213.8	2,285.7	1,149.5	8,105.0	2,603.8	940.2	-108.8	318.0	-209.3
Current_Orchard	Mo	61.6	26.5	10.6	61.4	27.4	10.0	-0.2	0.8	-0.6
Development	Mo	893.8	215.6	210.3	896.5	213.8	209.3	2.6	-1.7	-0.9
Fire	Mo	4,008.4	402.6	1,210.5	4,124.4	401.2	1,095.9	116.0	-1.4	-114.6
Natural_Land	Mo	10,591.5	11,809.1	2,965.5	10,546.7	11,886.3	2,933.2	-44.8	77.2	-32.3
	Island Ha Totals	***37,081.3***	***18,413.3***	***10,925.9***	***36,855.6***	***19,016.5***	***10,548.3***	***-225.7***	***603.2***	***-377.6***

Cause	Island	1999 Ha Grass	1999 Ha Woody	1999 Ha Bare	2016 Ha Grass	2016 Ha Woody	2016 Ha Bare	Grass Net Ha	Woody Net Ha	Bare Net Ha
Abandon_Animal_Use	Oa	2,516.9	1,318.1	377.8	2,481.2	1,337.6	394.1	-35.8	19.5	16.3
Abandon_Cultivated_Land	Oa	7,170.3	1,928.1	1,806.2	7,662.2	1,575.1	1,667.2	491.9	-353.0	-138.9
Abandon_Tree_Production	Oa	177.6	105.8	9.2	170.3	113.5	8.9	-7.4	7.7	-0.3
Current_Animal_Use	Oa	4,659.7	1,880.2	482.6	4,561.9	2,068.8	391.9	-97.9	188.7	-90.8
Current_Forestry	Oa	6.7	2.3	1.7	6.6	3.3	0.7	-0.1	1.0	-0.9
Current_Orchard	Oa	104.9	66.6	35.1	103.4	72.0	31.1	-1.5	5.4	-4.0
Development	Oa	24,104.8	3,479.2	6,710.5	24,407.9	3,483.6	6,403.1	303.1	4.4	-307.4
Fire	Oa	3,875.4	1,186.9	954.2	4,014.1	1,152.0	850.4	138.7	-34.9	-103.8
Natural_Land	Oa	38,146.8	39,675.7	5,847.8	37,608.1	40,244.5	5,817.7	-538.7	568.8	-30.1
	Island Ha Totals	***80,763.1***	***49,643.0***	***16,225.0***	***81,015.5***	***50,050.6***	***15,565.0***	***252.4***	***407.6***	***-660.0***

Cause	Island	1999 Ha Grass	1999 Ha Woody	1999 Ha Bare	2016 Ha Grass	2016 Ha Woody	2016 Ha Bare	Grass Net Ha	Woody Net Ha	Bare Net Ha
Abandon_Animal_Use	Ka	1,520.2	661.5	254.4	1,510.1	680.3	245.7	-10.1	18.8	-8.7
Abandon_Cultivated_Land	Ka	6,436.2	1,407.4	829.1	6,613.6	1,405.7	653.5	177.4	-1.7	-175.6
Abandon_Tree_Production	Ka	122.6	30.9	5.4	122.0	31.7	5.2	-0.6	0.9	-0.2
Current_Animal_Use	Ka	11,668.7	4,356.6	851.6	11,905.4	4,158.3	813.2	236.7	-198.3	-38.4
Current_Forestry	Ka	543.0	157.8	4.5	522.3	178.8	4.2	-20.8	21.0	-0.2
Current_Orchard	Ka	1,290.9	405.5	23.6	1,273.9	421.6	24.6	-17.1	16.1	0.9
Development	Ka	3,570.0	807.2	571.4	3,561.8	793.7	593.0	-8.2	-13.5	21.7
Fire	Ka	287.1	31.5	24.9	299.1	24.2	20.2	12.0	-7.3	-4.7
Natural_Land	Ka	39,448.3	48,480.6	13,757.2	39,412.2	48,588.8	13,685.1	-36.1	108.3	-72.1
Restoration	Ka	2.6	0.9	0.6	3.0	0.8	0.2	0.4	0.0	-0.4
	Island Ha Totals	***64,889.7***	***56,339.8***	***16,322.7***	***65,223.4***	***56,284.0***	***16,044.9***	***333.7***	***-55.8***	***-277.8***

Cause	Island	1999 Ha Grass	1999 Ha Woody	1999 Ha Bare	2016 Ha Grass	2016 Ha Woody	2016 Ha Bare	Grass Net Ha	Woody Net Ha	Bare Net Ha
Natural_Land	Ni	11,294.8	4,017.6	3,319.8	11,321.3	4,012.8	3,298.2	26.5	-4.8	-21.6

	1999 Ha Grass	1999 Ha Woody	1999 Ha Bare	2016 Ha Grass	2016 Ha Woody	2016 Ha Bare	Grass Net Ha	Woody Net Ha	Bare Net Ha
Statewide Totals	***677,448.9***	***449,420.2***	***453,190.1***	***670,884.5***	***456,958.4***	***452,216.2***	***-6,564.4***	***7,538.2***	***-973.9***

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