Title: Improved Wildfire Prediction Using Remote Sensing Technology on Guinea Grasslands in Hawaii

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Abstract

The synergistic impacts of nonnative grass invasion and frequent anthropogenic fire threaten endangered species and native ecosystems, and adjacent land throughout the tropics. It is generally accepted that these impacts result in landscape scale conversion from forest to grassland throughout the tropics. However, there is little published data to support this paradigm on a landscape scale on tropical islands, and no study has examined changes in fire potential following type conversion in these systems. If true, nonnative grasslands are more flammable than forests due to changes in fuel loads and microclimate and, thus, are at increased risk of fire occurrence and spread. Further, current predictive fire models do not accurately predict fire ignition or behavior in Hawaii's invasive grasslands, largely due to inadequate prediction of fuel moisture, a key driver of wildfire. The objectives of this research were to: (*i*) compare potential fire behavior in forests vs. grasslands, (*ii*) measure land cover change from 1950-2011 along two grassland/forest ecotones in Hawaii, and (*iii*) investigate the potential for using remotely sensed MODIS imagery to improve fuel moisture prediction. To address these objectives, we quantified fuel loads and moistures in nonnative forest and grassland (*Megathyrsus maximus*) plots (n=6), and used these field data to model potential fire behavior using the BehavePlus fire modeling program. Rate and extent of land cover change were quantified from 1950-2011 with historical imagery. Finally, we developed empirical models to predict real-time fuel moisture content in nonnative grasslands in Hawaii dominated by *Megathyrsus maximus* from Terra-MODIS NDVI and EVI2 vegetation indices.

Live and dead fuel moisture content and fine fuel loads did not differ between forests and grasslands, but mean surface fuel height was 31% lower in forests (72 cm) than grasslands (105 cm; P<0.02). However, predicted fire behavior differed greatly in forests vs. grasslands. Rates of spread were 3-5 times higher in grasslands (5.0-36.3 m min-1) than forests (0-10.5 m min-1) (P<0.001), and flame lengths were 2-3 times higher in grasslands (2.8-10.0 m) than forests (0-4.3 m) (P<0.01). Between 1950 and 2011, invasive grassland cover increased in heavily utilized grassland areas at both Makua (320 ha) and Schofield (745 ha) at rates of 2.62 and 1.83 ha yr-1, respectively, with more rapid rates of conversion before active fire management practices were implemented in the early 1990's. MODIS-based predictive models for live fuel moisture were modest (R^2= 0.46), and outperformed the currently used National Fire Danger Rating System (R^2= 0.37) and the Keetch-Byram Drought Index (R^2= 0.06). Dead fuel moisture prediction was less robust, and was best predicted by a model including EVI2 and NDVI (R^2= 0.19). These results support accepted paradigms for the tropics, and demonstrate that the type conversion associated with nonnative grass invasion and subsequent fire has occurred on a landscape scale. Moreover, once forests were converted to grassland there was a significant increase in fire intensity, likely providing a positive feedback to continued grassland dominance in the absence of active fire management. More accurate fuel moisture prediction in nonnative grasslands will greatly improve management of fire in Hawaii, as well as other tropical ecosystems dominated by nonnative grasses.

Background and purpose

Highly flammable African pasture grasses have been widely introduced throughout the tropics where they are now problematic invaders (D'Antonio and Vitousek, 1992; Williams and Baruch, 2000). In addition to impacting fire regimes, these invasive grasses commonly outcompete native plants for above- and belowground resources (Ammondt and Litton, 2012; Ammondt *et al.*, 2012), and alter carbon storage and forest structure (Litton *et al.*, 2006) and nutrient dynamics (Asner and Beatty, 1996; Mack *et al.*, 2001). These highly competitive grasses typically form a continuous layer of fine fuels, even under a forest canopy (LaRosa *et al.*, 2008), thereby increasing the potential for future fire and type conversion to nonnative grassland. Once a fire does inevitably occur, the postfire plant community is typically characterized by rapid nonnative grass regeneration, which then predisposes these ecosystems to more frequent and higher intensity fires as a result of increased fine fuel loads and changes in microclimate (Smith and Tunison, 1992; Pyne *et al.*, 1996; Blackmore and Vitousek, 2000; LaRosa *et al.*, 2008; Ainsworth and Kauffman, 2010). This cycle of nonnative grass invasion, fire, and grass reinvasion is a common occurrence in tropical ecosystems that leads to large scale land cover change (D'Antonio and Vitousek, 1992).

Plot level studies provide important insights into the relationships between nonnative grass invasion, fire, and type conversion from forest to grassland, but a greater understanding of these dynamics is only possible by examining these processes at the landscape scale (Brook and Bowman, 2006; Levick and Rogers, 2011). Furthermore, an understanding of the spatio-temporal dynamics of vegetation change over longer time scales can better elucidate the mechanisms driving vegetation change. Because the invasive grass–wildfire cycle has been so well documented at the plot scale, the dominant paradigm on tropical islands is that fire shifts composition from woody communities to nonnative grassland, that these changes persist over long time periods, and that the end result is a landscape that is increasingly dominated by nonnative invasive grasses that have a much higher fire risk than the forests that they replaced. However, few studies in the tropics have looked at landscape vegetation cover patterns resulting from repeated fire and grass invasion at larger scales (Blackmore and Vitousek, 2000; Grigulis *et al.*, 2005).

Fire modeling programs such as BehavePlus (Andrews *et al.*, 2005) and the National Fire Danger Rating System (NFDRS, (Schlobohm and Brain, 2002) were developed to simulate fire potential and behavior and to assist in predicting fire danger ratings, thereby providing fire managers with a suite of decision-making tools. The predictive capability of these models, however, depends largely on the accuracy of input variables such as fuel loads and fuel moisture, along with a suite of microclimate variables, all of which change rapidly over short temporal scales (Ellsworth et al, *in press*). The field method most commonly used for quantifying fuel moisture, a critical driver of fire occurrence and behavior, is to simply measure the proportion of fresh weight:dry weight of a number of samples collected from the site of interest. However, this method is time and labor intensive, and provides fuel moisture for only a snapshot in time. It would be useful for fire behavior prediction if fuel moisture for guinea grass could be estimated using remotely-sensed data, as has been done elsewhere for other vegetation types (Chuvieco *et al.*, 2002; Caccamo *et al.*, 2011).

Current tools used to predict live and dead fuel moisture on the mainland United States have not been widely tested in Hawaii against *in situ* fuel moisture data (Beavers, 2001), and it is unclear whether they accurately predict fuel moisture, and thus potential for fire. The National Fire Danger Rating System (NFDRS) is most commonly used by agencies in Hawaii as a tool to assess the potential for ignition, spread and difficulty of control. This index is based on the relationships between on-site fuels, weather, and topography and is calculated for each station within the Remote Automated Weather Station (RAWS) network (Schlobohm and Brain, 2002). Live and dead (1-hr) fuel moistures, in turn, are calculated as intermediates in the NFDRS and can also be obtained for any weather station in the network. The Keetch-Byram drought index (KDBI) is a meteorological index designed for predicting fire potential, and is based on the cumulative moisture deficiency in the upper layers of the soil profile (Keetch and Byram, 1968). While used widely for fire potential prediction, KBDI has been shown to be a poor to moderate predictor of fuel moisture content (Dimitrakopoulos and Bemmerzouk, 2003; Pellizzaro *et al.*, 2007; Caccamo *et al.*, 2011). KBDI is used more informally in Hawaii to assess longer term drying trends (A. Beavers, personal communication), typically in conjunction with the NFDRS.

The objectives of this study were to: (*i*) use field data and modeling to compare fuels and potential fire behavior in adjacent forests vs. grasslands, (*ii*) measure the rate and extent of land cover change at the grassland-forest boundary from 1950-2011 in and around two heavily utilized military installations on Oahu, Hawaii, and (*iii*) evaluate the use of vegetation indices derived from remotely sensed MODIS data to accurately predict live and dead fuel moistures in guinea grass dominated vegetation on leeward Oahu. We hypothesized that (*i*) fine fuel loads and heights would be lower and fuel moisture higher in forest plots than grass plots due to differences in understory microclimate (Hoffmann *et al.*, 2002) and shading (Funk and McDaniel, 2010); (*ii*) as a result of lower fuel heights and fuel loads, modeled fire behavior would be less severe (*i.e.* lower rates of spread, fireline intensity, flame lengths, and probability of ignition) in forest plots than grass plots (Freifelder *et al.*, 1998); (*iii*) rates of conversion from forest to grassland would increase through time over the past 50+ years due to increased ignition sources, and rates of conversion would be higher in areas where there was already a large grass component than in adjacent forests (Beavers, 2001); (*iv)* because vegetation indices are a good indicator of vegetation greenness, there will be strong relationships between vegetation indices derived from MODIS imagery and *in situ* live fuel moisture content; (*v*) because live and dead fuel moisture are closely correlated, we also expect moderate relationships between vegetation indices and dead fuel moisture content; *(vi)* because EVI performs well in areas of high biomass (Jensen, 2007), it will be a stronger predictor of fuel moisture than other vegetation indices given the dense grass cover present on our study sites; and *(vii)* daily MODIS data will show stronger predictive relationships with *in situ* fuel moisture than 8-day or 16-day composites, as fuel moisture can change rapidly within a site over a short time period, particularly following precipitation events (Ellsworth et al, *in press*).

Study description and location

Fuel Quantification

Fuel loads in guinea grass-dominated open grassland (grass sites) and adjacent nonnative forest (forest sites) were quantified in the summer of 2008 in the Waianae Kai Forest Reserve (forest: 367 m a.s.l.; MAP [mean annual precipitation], 1399 mm; MAT [mean annual temperature], 20ºC) (grass: 193 m.a.s.l.; MAP, 1134 mm; MAT, 23ºC) and Dillingham Airfield (forest and grass: 4 m a.s.l.; MAP, 900 mm; MAT, 24ºC; T. Giambelluca, *unpub. data*) on the Waianae Coast and North Shore areas, respectively, on the Island of Oahu, Hawaii, U.S.A. All sites are dominated by guinea grass in the understory. Forest sites at Waianae Kai Forest Reserve are dominated by nonnative trees, including *Leucaena leucocephala* (Lam.) De wit in the subcanopy and kiawe (*Prosopis pallida*) and silk oak (*Grevillea robusta*) in the overstory. Forest sites at Dillingham Airfield have dense nonnative *L. leucocephala* in the canopy, with infrequent other nonnative woody species scattered throughout. Soils at Dillingham Airfield are in the Lualualei series (fine, smectitic, isohyperthermic Typic Gypsitorrerts) formed in alluvium and colluvium from basalt and volcanic ash. Soils at Waianae Kai are in the Ewa series (fine, kaolinitic, isohyperthermic Aridic Haplustolls) formed in alluvium weathered from basaltic rock.

Within each of the two sites, three grassland and three forest plots were selected using USGS imagery in Google Earth 5.0. Plot selection was based on continuous grass cover and limited overstory trees for grassland plots, and a continuous tree overstory with guinea grass in the understory for forest plots. Final plot selection was made randomly from all possible locations that met these criteria. In each site, the following fuel variables were measured: (*i*) total fuel loads (standing live and dead, and litter), (*ii*) fuel composition (live grass, dead grass, shrubs, standing trees, downed wood), (*iii*) mean fuel height (calculated as 70% of maximum observed surface fuel height in each plot (Burgan and Rothermel, 1984)) and (*iv*) live and dead fine fuel moisture. In each plot, three parallel 50m transects were established 25m apart, and all herbaceous fuel was destructively harvested in six 25 x 50 cm sub-plots at fixed locations along each transect (n=18/plot). This sampling design adequately captured the spatial variability in fuels at a given site (Ellsworth et al, *in press*). Samples were immediately placed into sealed plastic bags to retain moisture. Within 6 hours of field collection, all samples were separated into categories (live grass, standing dead grass, surface litter, and downed wood), weighed, dried in a forced air oven at 70^{o}C to a constant mass (minimum 48 hours), and reweighed to determine dry mass and moisture content relative to oven dry weight.

Live standing trees and standing and downed dead wood were also quantified in each forest plot. The diameter at breast height (dbh) of all *L. leucocephala* trees– the dominant species in all forest plots – in a single 1 x 50 m belt transects was measured in each forest plot. Live tree biomass was determined using an existing species-specific allometric equation for *L. leucocephala* (Dudley and Fownes, 1992). The utility of this allometry for estimating biomass in trees from the Waianae Kai field site was explored by harvesting trees across the widest possible range of sizes found (n=20, dbh ranging from 1.5 to 6.2 cm dbh) and comparing observed vs. predicted biomass. There was a strong correlation between predicted and observed biomass (r^2= 0.95), indicating that the existing equation accurately estimates *L. leucocephala* biomass in our study sites. While other woody species occurred in the general study area, none were encountered in any of the sampling transects. Coarse downed woody fuels were sampled along three 50 m transects/plot using a planar intercept technique (Van Wagner, 1968; Brown, 1974). In addition, the height of the tallest blade of grass was measured in each subplot before clipping, and mean fine fuel height was recorded as 70% of the average maximum height across subplots (Burgan and Rothermel, 1984).

Fire Modeling

The fuels data described above were used to parameterize the BehavePlus 5 Fire Modeling System (Andrews *et al.*, 2005) to predict fire behavior for each plot. Live and dead fuel heat contents were measured by bomb calorimetry (Hazen Research, Inc., Golden, CO, USA). Previously published values of dead fuel moisture of extinction for guinea grass (Beavers, 2001) and woody surface area to volume ratio for humid tropical grasslands (Scott and Burgan, 2005) were used. Surface area to volume ratios for both live and dead fuels were measured on guinea grass individuals from Dillingham Airfield and Waianae Kai Forest Reserve (*n*=20 overall using a LI-3100C Leaf Area Meter (LI-COR Environmental, Lincoln, Nebraska) and water displacement. After examining wind speed data collected at the field sites, we selected an average 20-foot windspeed (15 km hr-1) and an extreme 20-foot windspeed (30 km hr-1) to simulate moderate and severe wind scenarios that were then applied to all sites. Wind adjustment factors of 0.4 and 0.3 were used for grass and forest plots, respectively, to adjust the windspeed collected by the RAWS weather stations (20-foot wind speed) to that at the vegetation height (surface wind speed) (Andrews *et al.*, 2005). Output variables of interest from the fire behavior model included: maximum rate of spread (ROS; m min-1), fireline intensity (kW m-1), flame length (m), and probability of ignition (%).

Historical and Spatial Land Cover Change Analysis

Land cover classifications were made on orthorectified aerial photographs and high resolution multispectral Worldview-2 imagery for Makua Military Reservation (108 m.a.s.l.; MAP, 864 mm; MAT, 23ºC) and Schofield Barracks (297 m.a.s.l.; MAP, 1000 mm; MAT, 22ºC; (Giambelluca *et al.*, 2011); Figure 1). Classified maps for Makua were derived from images for five time periods: 1962, 1977, 1993, and 2004 aerial photographs, and 2010 Worldview-2 scenes. Schofield land cover maps were created for six time periods: 1950, 1962, 1977, 1992, and 2004 aerial photographs, and 2011 Worldview 2 scenes. The 2004 images for Makua and Schofield were high resolution (0.3 m) USGS registered images with a positional accuracy that did not exceed 2.12 m RMSE (root mean square error). The other images were registered to the 2004 images with a first-order polynomial warping (affine transformation) to achieve an average RMSE of 3.37 m and a maximum RMSE of 9.84 m. Worldview-2 images are high resolution (~0.5 m) with a positional accuracy of 12.2 m at the CE90 level.

Both Makua and Schofield site boundaries were digitized into polygon vector shapefiles using ArcGIS Desktop Version 9.3.1 (ESRI, Redlands, California, USA). Each site was divided into two areas of interest (AOI): a grassland area within the fire break which is heavily utilized for military training activities and a forested area outside the fire break, where little military activity occurs. While these areas were defined as grassland vs. forest, respectively, each contains patches of both grass and woody cover as well as patches of more intensive utilization (*i.e.* developed military training areas). The ArcGIS Data Management tool *Create Fishnet* was used to divide the study sites into grids with a 50 x 50 m cell size and clip the grids to the site boundaries. After the grids were created, they were overlaid onto the images for classification.

Each cell was classified into one of seven cover classes at Makua: Grass, shrub, forest, bare, developed, military training area (MTA; highly disturbed area with minimal vegetative cover), and shadow/cloud (treated as No Data). The woody plant composition at Schofield is highly variable and forest and shrub cover classes are often indistinguishable from aerial images. At Schofield, therefore, shrub and forest cover classes were combined into a single mixed woody cover class, resulting in only six cover classes for this site (grass, woody, bare ground, developed, MTA, and No Data). The total area of each cover class was calculated for every time period within the two AOIs for both sites. Amounts and rates of land cover change (expressed as average hectares per year) were then extrapolated for each of the four AOIs over each time period.

In situ *fuel moisture data collection*

Bi-weekly *in situ* fuel moisture samples were collected from October 2009-October 2010 in guinea grass dominated ecosystems at Schofield Barracks, Yokohama State Park, and Dillingham Ranch on the Island of Oahu, Hawaii. All sites are dominated by guinea grass with some invasive *Leucaena leucocephala* (Lam.) De wit in the overstory. Yokohama (7 m.a.s.l.; MAP = 857 mm; MAT = 24ºC), soils are in the Lualualei series, (fine, smectitic, isohyperthermic Typic Gypsitorrerts) formed in alluvium and colluvium from basalt and volcanic ash. Schofield Barracks and Dillingham Ranch sites are discussed above.

On the first sampling date in October 2009, a single 50m transect was established in each site. Starting at the 0m mark of each transect, biomass of all herbaceous plant materials occurring in a 25x50 cm plot was clipped at the soil surface every 10m along the transects (*n*=6/transect). Samples were taken back to the laboratory and separated into the following categories: live herbaceous vegetation, dead herbaceous vegetation and surface litter. Samples were then weighed, dried in a forced air oven at 70^{o}C to a constant mass, and re-weighed. Fuel moisture was the calculated as the ratio of the weight of water to the dry weight of the plant material, expressed as a percentage. Subsequent weeks' sampling occurred on parallel transects, with each biweekly sampling offset from the prior sampling transect by 1 m.

MODIS data acquisition and processing

MODIS data products were acquired from the NASA Earth Observing System Data and Information System (http://reverb.echo.nasa.gov/reverb/) for all dates corresponding to *in situ* sampling. The datasets used in our analyses included the following: Surface Reflectance Daily L2G Global 250m (MOD09GQ), Surface Reflectance Daily L2G Global 1km and 500m (MOD09GA), Surface Reflectance 8-day Global L3 Global 250m (MOD09Q1), Surface Reflectance 8-day L3 Global 500m (MOD09A1), and Vegetation Indices 16-day L3 Global 250m (MOD13Q1). Each data product was available in the sinusoidal projection. We used the MODIS Reprojection Tool (NASA Land Processes Distributed Active Archive Center [LP DAAC], USGS/Earth Resources Observation and Science [EROS] Center, Sioux Falls, South Dakota) to project the data into the Universal Transverse Mercator projection zone 4 on the North American Datum 1983. ENVI 4.5 (Exelis Visual Information Solutions, Boulder, Colorado) was used to reformat the data into a multi-date image cube and create a temporal profile of reflectances for each band at each study site location.

Vegetation indices

Vegetation indices of interest – including NDVI, EVI, EVI2, VARI, NDWI, NDII, RGRE, and an integral calculation (Chuvieco *et al.*, 2002) – were calculated separately for daily and 8-day reflectance values for the entire one year study period. 16-day NDVI and EVI vegetation index products were also obtained, as well as reflectance values for bands 1-3.

MODIS 16-day composite data omits bands 4-7, allowing calculations of only a subset of the vegetation indices (EVI2 and RGRE) for this temporal resolution.

NFDRS fuel moisture and KDBI

KDBI values and NFDRS (1978 system) calculations for live and dead fuel moisture for each *in situ* sampling date were retrieved on June 14, 2012 from the Weather Information Management System (WIMS), which is maintained by the National Wildland Coordinating Group (https://fam.nwcg.gov/wims/jsp/wims.htm). Weather data used in WIMS calculations was measured near each field site using the RAWS network (WIMS tower ID #'s 490308, 490301, and 499902 were used for Dillingham, Yokohama, and Schofield sites, respectively).

Statistical Analyses

General linear models were used to determine whether there were differences in live and dead fine fuel loads, fine fuel moistures, average fuel height, fire behavior variables (ROS, fireline intensity, flame length) and probability of ignition between grassland and forest plots, after controlling for differences in mean annual precipitation (MAP) among sampled plots. Because there is an elevation/ precipitation gradient at Waianae Kai Forest Reserve, and forest plots were clustered ~150 m higher in elevation than grassland plots, MAP was included in the model to control for differences in environmental variables that may have potentially impacted fuels and fire behavior. Site was treated as a random factor, plot type (forest or grassland) was treated as a fixed factor, and MAP was used as a covariate. Live and dead fine fuel variables were log-transformed for analysis to meet model assumptions of normality and homogeneity of variance, but all results are presented herein as untransformed data. Minitab v. 15 (Minitab, Inc., State College, PA) was used for all statistical analyses, and significance was assessed at $\alpha=0.05$. For Fragstats spatial analyses, AOI's within sites are not independent, and only two sites were analyzed, making statistical inference inappropriate. Therefore, this analysis was limited to an examination of temporal trends in patterns.

Pearson correlation coefficients were calculated with all sites pooled to describe the strength of the relationship between each daily, 8-day, and 16-day vegetation index with live, dead, and litter fuel moisture. Because WIMS calculations and fire prediction tools (*i.e.* BehavePlus) do not separate standing dead and surface litter fuel components, measurements for dead fuel moisture were weighted by the proportion of the two dead fuel components and examined in all analyses as a single variable. All significant correlations were further examined individually and in combination using general linear regression models to identify the strongest MODIS-based predictor variable(s) for *in situ* live and dead fuel moisture for each temporal scale (daily, 8-day, and 16-day). Similarly, the ability of WIMS-calculated KBDI and fuel moisture (live and dead) to predict *in situ* fuel moisture was examined using general linear models. Finally, the best predictor variables for both MODIS-based and WIMS-based were evaluated in hybrid models to determine the strongest predictive relationships between all available fuel moisture predictors and *in situ* measured live and dead fuel moisture at each temporal scale. We were most interested in a general model that accurately predicts live and dead fuel moisture across all guinea grass ecosystems on leeward Oahu, Hawaii. However, because these nonnative, invasive guinea grass ecosystems are high fire risk areas, we also evaluated the inclusion of a site term in the best predictor model to test whether there was greater capacity to accurately predict fuel moisture at a single site than across the larger area of interest.

Key findings

Fuel Quantification

After controlling for differences in MAP (*P*<0.01), there were **few differences in fine fuels between forest and grassland plots**, with live fine fuels ranging from 2.1-5.9 Mg ha-1(*P*=0.86), and dead fine fuels ranging from 10.4-19.5 Mg ha-1 (*P*=0.89; Table 1). MAP was a strong predictor of both live (*P*=0.02) and dead (*P*=0.05) fuel moisture, and there was no evidence of differences in fuel moistures between forest and grassland (live, *P*=0.19*;* dead, *P*=0.95). Live fine fuel moisture at the time of sampling ranged from 47-173%, and dead fine fuel moisture from 14-65%. **Mean fuel height, however, was 31% lower in forests (72 cm) than in grasslands (105 cm; *P*<0.02)** after accounting for differences in MAP (Table1).

Fire Modeling

Despite holding microclimate constant and fuels only differing between forest and grassland in terms of height, **predicted fire behavior differed greatly between these two land cover types** (Table 2). Under moderate wind conditions (15 kph), rate of modeled fire spread was 3-5x higher in grassland (5.0-17.7 m min-1) than forest (0-5.0 m min-1) (*P*<0.001), and flame lengths were 2-3x higher in grassland (2.8-7.2 m) than forest (0-3.0 m; *P*<0.01). Fireline intensity at moderate wind conditions was also higher in grassland (2,426-19,034 kW m-1) than forest (0-2,914 kW m-1) (*P*<0.01). Under extreme wind conditions (30 kph), predicted rates of spread were 3-10x higher in grasslands (10.1-36.3 m min-1) than in forests (0-10.5 m min-1) (*P*<0.001); flame lengths were 2.5-4x higher in grasslands (3.9-10.0 m) than forests (0-4.3m) (*P*<0.01); and fireline intensity was higher in grasslands (4,919-39,004 kW m-1) than in forests (0-6,166 kW m-1) (*P*<0.01). Probability of ignition ranged from 0-32% and did not differ between cover types under either moderate or extreme wind conditions (*P*=0.27) (Table 2).

Historical and Spatial Land Cover Change Analysis

Invasive grassland cover increased in heavily utilized areas inside the firebreak at both Makua (total area of 320 ha) and Schofield (total area of 745 ha) at rates of 2.62 and 1.83 ha yr-1, respectively, over the entire 50+ years examined, with more rapid rates of conversion (up to 7.41 ha yr-1) occurring before aggressive fire management practices were implemented in the early 1990's (Table 3; Figures 1-2). At Makua, conversion from forest to grassland in the surrounding forest area (total area of 1244 ha) was slower (1.78 ha yr-1) than in the grass area (Figure 1). Unlike Makua, in the forest area at Schofield (total area of 1576 ha) conversion of grassland to forest occurred at a faster rate (4.75 ha yr-1) than in grass areas (Figure 2). Overall, change in land cover over time was more dynamic at Makua (Figure 1) than at Schofield (Figure 2), coinciding with large and frequent fires at Makua, and fewer acres burned at Schofield.

In situ *fuel moisture*

Live and dead fuel moistures were dynamic throughout the sampling period, ranging from 45 to 294% and 6 to 49%, respectively, and sometimes changing rapidly between biweekly sampling dates. Schofield, which had the highest MAP, generally had the highest live and dead fuel moisture of all sites, and live fuel moisture at this site never dropped below 122%. In contrast, the Dillingham and Yokohama sites, which are located at lower elevations and lower MAP, had frequent periods where live fuel moisture dropped well below 100%. Seasonal patterns were similar across all sites, with highest fuel moistures in the winter months, and periods of low fuel moisture in the drier summer and fall months (Figure 3).

MODIS-based fuel moisture correlations

Vegetation indices calculated from daily MODIS data were also dynamic (Figure 3) and none were correlated with live, dead, or litter fuel moisture (Table 4; Figure 3), except daily EVI values, which were positively and linearly correlated with live fuel moisture (r = 0.338; P=0.001). Vegetation indices calculated from 8 day composite MODIS data had somewhat clearer seasonal patterns (Figure 4) and stronger relationships with *in situ* fuel moisture measurements, with EVI, NDVI, and EVI2 all showing significant relationships with live, dead, and litter fuel moisture (P<0.01; Table 4). EVI had the strongest relationship with live fuel moisture (r = 0.399; P<0.001), while EVI2 had a stronger relationship with dead fuel moisture components (r = 0.379; P<0.001 for standing dead, and r = 0.380; P<0.001 for litter fuel moisture). 16-day composite MODIS vegetation index products were positively and linearly correlated with live, dead, and litter fuel moisture (Table 4; Figure 4). NDVI had the strongest relationship with live fuel moisture (r = 0.462; P<0.001), and EVI2 had stronger correlations with standing dead (r = 0.450; P<0.001) and litter (r = 0.374; P<0.001) fuel moisture.

MODIS-based fuel moisture models

Empirical models were derived from the MODIS-based vegetation indices (EVI, EVI2, and NDVI) that were most strongly correlated with fuel moisture at each temporal scale (Table 1; daily, 8-day, 16-day). Each vegetation index was analyzed alone and in all possible combinations to determine the strongest predictive relationships. Using daily vegetation index data, EVI alone had the strongest linear relationship with live fuel moisture (R^2 = 0.15; p<0.001; Table 5), but no predictive power (R^2_{pred} = 0.00), and no relationship with dead fuel moisture (R^2 = 0.00; R^2_{pred} = 0.00; p=0.082; Table 6). No other daily VI's alone or in combination generated models that accurately predicted dead fuel moisture. The best relationships using 8-day composite data for both live (R^2 = 0.20; R^2_{pred} = 0.15; p<0.001; Table 2) and dead (R^2 = 0.14; R^2_{pred} = 0.06; p=0.001) fuel moisture contained both EVI and NDVI. 16-day composite indices had the strongest relationships with both live and dead fuel moisture of all MODIS-based models examined. **Best MODIS-based predictive models for both live (R^2 = 0.46; R^2_{pred} = 0.40; p<0.001; Table 5) and dead fuel moisture (R^2 = 0.19; R^2_{pred} = 0.12; p=0.002; Table 6) included EVI2 and NDVI.**

WIMS-based algorithms, which are currently used in fire planning and management in Hawaii, were poor predictors of *in situ* fuel moisture measurements compared with MODIS-based models. NFDRS predictions of live fuel moisture had slightly weaker relationships with *in situ* measurements (R^2 = 0.37; R^2_{pred} = 0.33; p<0.001; Figure 5) than MODIS-derived predictions (Table 5). There was no relationship between NFDRS predicted and *in situ* dead fuel moisture (R^2 = 0.05; R^2_{pred} = 0.00; p=0.066; Table 6; Figure 4). KDBI was an even poorer predictor of both live (R^2 = 0.06; R^2_{pred} = 0.01; p=0.050; Table 5) and dead (R^2 = 0.01; R^2_{pred} = 0.00; p=0.477) fuel moisture (Table 6).

Hybrid models (containing both MODIS and WIMS components) were generally stronger predictors of *in situ* fuel moisture than either MODIS or WIMS models alone (Table 5). **The strongest overall predictor of live fuel moisture used 8 day MODIS EVI as well as NFDRS and KBDI data** (R^2 = 0.49; R^2_{pred} = 0.41; p<0.001; Figure 7), which represents only a slight improvement over the MODIS-only model. Hybrid models for dead fuel moisture (R^2_{pred} = 0.00 for all models) did not offer improvements over the best MODIS-only model (Table 6; Figure 8).

All models presented above are generalized across all study sites, but in some cases a site specific model yielded stronger relationships with *in situ* fuel moisture. When a site factor was added to the best MODIS-based model (16 day composite VI), additional variability was explained by the model (R^2 = 0.61; R^2_{pred} = 0.59; p<0.001), adding considerable predictive power. Similarly, adding a site factor to the NFDRS model for live fuel moisture prediction improved model fit (R^2 = 0.42; R^2_{pred} = 0.39; p<0.001). Dead fuel moisture models were not improved by the inclusion of a site factor.

Management implications

1. While type conversion from forest to grassland has occurred, active fire management can offset, and even reverse this trend.

These results clearly show that the areas studied have experienced large type conversions from forest to grassland over the past 50+ years. This conversion to grasslands, in turn, altered fuel heights and increased modeled fire spread and intensity, which likely represents a positive feedback to grassland dominance (i.e., the invasive grass-wildfire cycle). On a landscape scale, however, the interactions among fire, grass invasion, nonnative woody species and fire management appear to be much more complex. Because it is generally accepted that repeated fires and the presence of nonnative grasses lead to a landscape that is increasingly dominated by flammable grasslands, we expected to see an increase in the rate and extent of conversion in more recent years as compared to historical landscapes. While we acknowledge that the two valleys analyzed in this study do not mirror all landscapes in the tropics, they do represent among the most highly impacted end of the spectrum in terms of utilization intensity and opportunities for fire ignition (i.e., frequent military training activities). Because of this, we expected to see rapid rates of land cover conversion. The mean trend over time in grassland areas at both sites was a reduction in woody cover with a concomitant increase in grassland cover, as originally hypothesized. This was expected, as these areas are heavily utilized by military training activities, and ignitions from training are frequent. In the forests, however, there were different trends observed over time. At Makua, where fires have been larger and more frequent, the forest is slowly being replaced by grassland. Fire management has been exceedingly difficult at this site (Beavers *et al.*, 1999) due to low precipitation and fuel moisture, remoteness, intensity of military training, and common anthropogenic ignitions (*i.e.* arson, roadside). In 2004, all live fire training stopped at Makua to address fire concerns at this site, but several human ignited fires have since occurred.

At Schofield, however, the pattern of change over time in the forest was very different from Makua. Grass cover steadily decreased from 1950 to the present, while woody species, and to a lesser extent, military training areas, increased. While this area is inaccessible due to unexploded ordinance, we presume that most of the woody increase is due to the spread of nonnative woody species, rather than a recovery of a very limited native plant component in the area. Several factors may contribute to the differential response at Schofield. This site has ~16% higher precipitation than Makua (Giambelluca *et al.*, 2011), with higher fuel moistures (Ellsworth et al, *in review*). Additionally, fire managers at Schofield have been successful at containing fires within the fire break perimeter since improved fire management began in the 1990's. A well trained fire crew is housed on this instillation, and a well-designed fire management plan has largely limited severe wildfires (Beavers and Burgan, 2001).

2. Remotely sensed vegetation index data are better predictors of fuel moisture than currently used models for nonnative *M. maximus*-dominated grasslands in Hawaii

While MODIS-based models for live fuel moisture content showed only moderate improvements over WIMS-based models, an important additional advantage of this method is the continuous spatial coverage provided by satellite data. The RAWS network has weather stations throughout the U.S., providing frequent points from which WIMS-based models can be extrapolated (http://www.raws.dri.edu/). However, fires commonly occur in remote areas, and there are large regions, particularly in Hawaii, with no RAWS coverage. In addition, many areas, including Hawaii, have very steep topography, where important weather variables such as precipitation and relative humidity change rapidly with spatial position (Giambelluca *et al.*, 2011), making accurate moisture prediction limited to small areas near RAWS towers. Further, sensors on weather towers frequently are inoperable or have sensors that have not been calibrated in years and, thus, commonly transmit inaccurate data which requires a thorough quality assurance protocol on all data used – a time expenditure that few fire managers can justify. In this study, for example, of all WIMS data points corresponding to *in situ* fuel moisture measurements (N=116), only 62% of them (N= 72) could be used in the analysis of models including WIMS data due to sensor or data transmission failure.

While MODIS-based models had stronger relationships with fuel moisture than WIMS-based models, the best predictive model for live fuel moisture included components of both systems. The problems associated with the WIMS measurements (proximity to RAWS station, data quality) discussed above, however, should be carefully evaluated before using these hybrid models to predict fuel moistures. The slight advantage of using the hybrid model (R^2_{pred} =0.40) over the MODIS-based model (R^2_{pred} =0.41) is likely not enough to warrant the additional trouble of assuring good WIMS data. Dead fuel moisture was best predicted using a model based on MODIS data alone, eliminating the uncertainties associated with using WIMS data.

Issues with spatial continuity should also be considered before developing a site-specific model for fuel moisture prediction. In this paper, there was improved predictive capability (*i.e.* R^2_{pred} =0.59 vs. R^2_{pred} =0.40) of some models when a site term was included, but due to the rapid change in topography and, thus, climate in many areas of Hawaii (Giambelluca *et al.*, 2011), site specific models should be used only with extreme caution outside of the area where *in situ* fuel moisture measurements were taken and the models were developed.

It was expected that there would be a tradeoff between accuracy in spatial and temporal resolution of fuel moisture content when weather station models were compared to MODIS-based models. Our hypothesis that daily MODIS data would be the best predictor of fuel moisture, however, was not supported by our data. Instead, the **best MODIS-only predictive models for both live and dead fuel moisture were developed using the 16-day composite data**. We expect that this result is a function of improved accuracy of each pixel value in the composite images outweighing the benefits of better temporal resolution of changes in vegetation phenology. This finding provides an **unexpected additional benefit for fire managers, as the 16-day composites are easily accessed and freely downloadable from the internet**.

Relationship to other recent findings and ongoing work on this topic

Our results show that increased fuel bed depth and an increased effect of wind at the fuel surface (Freifelder *et al.*, 1998; Andrews *et al.*, 2005) in grassland has led to the potential for much more intense fire behavior compared to forest. These data support previous work in Hawaii (Hughes *et al.*, 1991; Freifelder *et al.*, 1998), and elsewhere in the tropics (Williams and Baruch, 2000; Hoffmann *et al.*, 2002; Rossiter *et al.*, 2003), demonstrating that, at the plot level, the synergistic effects of fire and nonnative grass invasion can lead to a pervasive invasive grass-wildfire cycle. From this study, it can be inferred that at a landscape scale, the grass-wildfire cycle may not be the final endpoint for all fire impacted and nonnative grass invaded tropical ecosystems, as is currently the paradigm in the science and management communities. A recent review of the impacts of woody invasive plants on fire regimes (Mandle *et al.*, 2011) showed that, while most discussion centers around the effects of grass invaders, invasive woody plants can also alter ecosystem properties and patterns, thereby impacting future fire regimes. A dominant nonnative woody invader in the forested area at Schofield, *Schinus terebinthifolius* Raddi (christmasberry) (Beavers and Burgan, 2001), may reduce fire temperature and spread (Beavers and Burgan, 2001; Stevens and Beckage, 2009), potentially offering an escape from the grass-wildfire cycle (Mandle *et al.*, 2011). While our results show that grasslands are prone to more extreme fire behavior than forests, it was not always the case that increased flammability led to widespread increases in grassland cover across the landscape. In fact, many areas appear to be recovering a woody overstory, albeit nonnative, suggesting that active fire management is largely preventing further type conversion to nonnative grasslands.

The predictive capability of MODIS vegetation index data shown in our research support similar work in shrubland, forest, and heathlands in Australia (Caccamo *et al.*, 2011), where MODIS data better predicted live fuel moisture (R^2= 0.69) than the commonly used KDBI predictors (R^2= 0.15). Strong relationships were also shown between remotely sensed VI's and live fuel moisture in several Mediterranean vegetation types ($0.72<R^2< 0.82$) (Chuvieco *et al.*, 2002) and in Coastal Plains in Georgia, USA (r =0.57-0.96) (Hao and Qu, 2007). While our results showed improvement over the current system for live fuel moisture prediction in Hawaii, the relationships were weaker than those typically found elsewhere. A possible explanation for this is that there is a large amount of standing dead guinea grass, particularly during drier months (Ellsworth et al, *in press*), making moisture content and, thus, reflectance signatures over an area represented by one pixel quite variable, as described by Danson and Bowyer (2004).

Dead fuel moisture content in non-native M. maximus grasslands in Hawaii was not well predicted by any of the models tested. We hypothesized that vegetation indices would be stronger predictors of live fuel moisture than dead, but expected a better model for dead fuel moisture, as both live and dead fuel moistures change seasonally with precipitation events (Ellsworth et al *in press*). While several previous studies have evaluated various remotely sensed greenness-based data products for their ability to predict live (Danson and Bowyer, 2004; Hao and Qu, 2007; Caccamo *et al.*, 2011) and total fuel moisture content (Chuvieco *et al.*, 2002), few have looked at the relationships with dead fuels alone (Nieto *et al.*, 2010). In tropical grassland ecosystems, dead fuels can make up well over half of the total fine fuel loads ((Kauffman *et al.*, 1998, Ellsworth et al *in press*), and play a predominant role in driving fire behavior. Despite this limitation of using MODIS-derived products to accurately predict dead fuel moisture content in these systems, our results show that the current WIMS-based prediction systems (NFDRS, KDBI), which are commonly used in fire management today, do an even poorer job of predicting dead fuel moisture content in these ecosystems.

Future work needed

1. Similar research in other dominant invasive grass species in Hawaii

Guinea grass is one of the more problematic invasive grass species in the Hawaiian Islands, but several others pose significant fire risk as well (*i.e*., fountain grass, *Pennisetum setaceum;* molasses grass, *Melinis minutiflora;* and buffelgrass, *Pennisetum ciliare*). Investigations into the differences in fuels characteristics, fire spread, and the potential for using remote sensing data for fuel moisture prediction in these additional grassland ecosystems would better enable fire managers to make landscape scale fire risk assessments.

2. Further testing of MODIS fuel moisture prediction system in guinea grass ecosystems throughout the tropics

While this method has been shown to be an improvement on existing methodology for fuel moisture prediction in Hawaii, it did not perform as well as has been seen in temperate ecosystems. Some possible explanations for this may the large amount of standing dead guinea grass, particularly during drier months making moisture content and, thus, reflectance signatures quite variable within a single pixel. Further investigations in grass-dominated ecosystems throughout the tropics would be a valuable next step.

3. Additional investigation into site specific models for local land manager's use.

One of our objectives was to create models that were useful over a wide geographical range, however, site specific models had greater predictive capability than did the more general model. In areas where frequent fire ignitions are likely, it may be useful to have site specific models built to more precisely predict fuel moisture.

4. Development of a user-friendly web-based interface to access MODIS outputs.

Work is currently in progress to develop a web-based, user-friendly interface to make the readily accessible, freely available technologies presented in the current research more attractive to land and fire managers. Currently there is a fair bit of technical jargon and several downloadable webtools that are used in the data processing protocol. For land managers to be attracted to this technology, it would be very useful to streamline the processing to a single web interface.

Table 1. Live and dead fine fuel loads (in Mg ha-1), fuel moisture (%), and maximum fuel height (cm) in open guinea grass ecosystems and forested ecosystems with a guinea grass understory on leeward Oahu, Hawaii. Means and standard errors are given for fuels variables at each site (*N*=3). Significant model factors are indicated by bold font in the last three columns.

Variable	**Dillingham Grass**	**Dillingham Forest**	**Waianae Kai Grass**	**Waianae Kai Forest**	**Model R^2 (%)**	**MAP**	**Site**	**Type**
							(P-value)	
live fine fuels	4.6 (0.9)	5.9 (3.9)	3.7 (0.4)	2.1 (1.0)	31.1	0.38	0.65	0.86
dead fine fuels	19.5 (4.3)	19.5 (3.0)	13.7 (0.6)	10.4 (1.8)	51.4	0.52	0.80	0.89
live fuel moisture	47.2 (3.6)	78.2 (13.1)	57.7 (9.0)	173.6 (27.3)	84.2	**0.02**	0.18	0.19
dead fuel moisture	13.6 (2.3)	23.4 (6.8)	15.5 (2.9)	65.2 (31.4)	61.7	**0.05**	0.14	0.95
max. fuel height	138.6 (9.7)	71.0 (3.0)	71.3 (10.7)	72.3 (12.0)	76.5	**0.02**	**<0.01**	**<0.01**

Table 2. Predicted fire behavior under both moderate (15 kph) and severe (30 kph) wind conditions in open guinea grass ecosystems and forested ecosystems with a guinea grass understory on leeward Oahu, Hawaii. Means and standard errors are given for fire behavior variables at each site (*N*=3). Significant model factors are indicated by bold font in the last three columns.

Variable	**Wind condition**	**Dillingham Grass**	**Dillingham Forest**	**Waianae Kai Grass**	**Waianae Kai Forest**	**Model R^2 (%)**	**MAP**	**Site (P-value)**	**Type**
Rate of Spread	moderate	14.9 (1.6)	2.7 (1.2)	5.8 (0.6)	0.4 (0.4)	91.0	**0.04**	**<0.01**	**<0.001**
(m min -1)	severe	30.7 (3.1)	5.7 (2.6)	12.0 (1.2)	0.8 (0.8)	91.1	**0.04**	**<0.01**	**<0.001**
Flame Length	moderate	5.8 (1.0)	2.1 (0.5)	3.0 (0.2)	0.3 (0.3)	84.8	0.61	0.10	**<0.01**
(m)	severe	8.1 (1.4)	2.9 (0.8)	4.3 (0.3)	0.4 (0.4)	84.6	0.62	0.11	**<0.01**
Fireline Intensity	moderate	12829 (4075)	1503 (750)	2983 (537)	57.7 (57.7)	71.3	0.13	**0.04**	**<0.01**
(kW m-1)	severe	26355 (8298)	3154 (1598)	6135 (1084)	123.7 (123.7)	71.5	0.13	**0.04**	**<0.01**
Probability of	moderate	21.0 (7.0)	10 (10)	14.3 (5.6)	0.3 (0.3)	38.5	0.84	0.82	0.27
Ignition (%)	severe	21.0 (7.0)	10 (10)	14.3 (5.6)	0.3 (0.3)	38.5	0.84	0.82	0.27

Table 3. Rates of land cover change at Makua Military Reservation and Schofield Barracks from 1950 to 2011. Change is given in units of average hectares per year for each date range. Total size for study areas are as follows: Schofield Grass, 745 ha; Schofield Forest, 1576 ha, Makua Grass, 320 ha; and Makua Forest, 1244 ha.

		1950-1962	**1962-1977**	**1977-1992**	**1992-2004**	**2004-2011**	**1950-2011 (mean)**
Schofield Grass	grass	3.0	1.2	2.6	0.7	-5.5	1.2
	woody	-2.0	-0.7	-3.2	-1.5	-4.6	-2.1
	bare ground	0.0	-0.1	0.0	0.2	-0.5	0.0
	developed	0.0	0.0	0.0	0.0	0.0	0.0
	shadow	0.0	0.0	0.0	0.0	0.0	0.0
	MTA	-1.0	-0.4	0.5	0.6	10.6	0.9
Schofield Forest	grass	-8.4	-7.3	-2.7	-1.0	-1.1	-4.5
	woody	-0.7	10.8	5.3	0.6	0.7	4.0
	bare ground	0.9	-0.9	0.0	0.4	-0.7	0.0
	developed	0.0	0.0	-0.4	-0.2	0.9	-0.1
	shadow	8.5	-4.3	-2.7	0.0	0.0	-0.1
	MTA	-0.3	1.8	0.5	0.2	0.1	0.5
			1962-1977	**1977-1993**	**1993-2004**	**2004-2010**	**1962-2010 (mean)**
Makua Grass	grass		7.4	5.0	-6.3	6.8	3.4
	shrub		-5.7	-6.6	8.1	-6.7	-3.0
	tree		-1.9	0.2	-0.2	0.0	-0.6
	bare ground		0.2	0.7	-1.1	-0.1	0.0
	developed		0.0	0.0	0.0	0.0	0.0
	shadow		0.0	0.0	0.0	0.0	0.0
	MTA		0.0	0.8	-0.5	0.0	0.2
Makua Forest	grass		0.8	9.5	-2.3	10.6	4.2
	shrub		2.0	-1.0	3.9	-19.9	-1.3
	tree		1.0	-1.4	3.3	8.7	1.7
	bare ground		0.4	-0.2	0.1	0.0	0.1
	developed		0.0	0.0	0.0	0.0	0.0
	shadow		-4.2	-6.8	-4.9	0.5	-4.6
	MTA		0.0	0.0	0.0	0.0	0.0

Table 4. Pearson correlation coefficents (*r*) showing the strength of the relationships between Terra-MODIS derived daily, 8-day, and 16-day vegetation indices for guinea grass ecosystems on Oahu, Hawaii. Bold font indicates values that are statistically significant at the P<0.05 level.

	Live		**Dead**		**Litter**	
	r	P-value	r	P-value	r	P-value
Single day						
EVI_1	**0.338**	**0.001**	0.170	0.093	0.184	0.069
NDVI_1	0.088	0.368	-0.015	0.875	-0.019	0.844
EVI2_1	0.081	0.410	0.033	0.733	0.035	0.717
VARI_1	0.165	0.100	0.075	0.456	0.084	0.404
NDWI_1	-0.026	0.787	0.045	0.642	0.083	0.398
NDII_1	0.037	0.704	0.186	0.056	0.150	0.123
RGRE_1	0.055	0.576	0.045	0.643	-0.005	0.960
Integral_1	0.105	0.282	0.142	0.144	0.124	0.204
8 day						
EVI_8	**0.399**	**0.000**	**0.333**	**0.000**	**0.280**	**0.003**
NDVI_8	**0.347**	**0.000**	**0.309**	**0.001**	**0.403**	**0.000**
EVI2_8	**0.328**	**0.000**	**0.379**	**0.000**	**0.380**	**0.000**
VARI_8	0.098	0.307	0.028	0.770	0.040	0.676
NDWI_8	0.020	0.837	0.120	0.211	0.016	0.871
NDII_8	0.139	0.144	**0.220**	**0.020**	0.160	0.093
RGRE_8	**0.274**	**0.003**	0.140	0.139	**0.268**	**0.004**
Integral_8	-0.101	0.287	-0.051	0.590	**-0.200**	**0.033**
16 day MODIS products						
EVI_16	**0.364**	**0.001**	**0.423**	**0.000**	**0.325**	**0.003**
NDVI_16	**0.462**	**0.000**	**0.362**	**0.001**	**0.329**	**0.002**
EVI2_16	**0.449**	**0.000**	**0.450**	**0.000**	**0.374**	**0.001**
RGRE_16	**0.398**	**0.000**	0.049	0.663	0.119	0.283

Table 5. Models predicting *in situ* live fuel moisture. MODIS-based models were generated from remotely sensed Terra-MODIS daily, 8-day composites, and 16-day vegetation index data. WIMS-based models are calculated from onsite weather data. Hybrid models were developed using the best predictors from both MODIS and WIMS-based models. Bold font indicates strongest and recommended models.

	Model	R^2	**Pred** R^2	P
MODIS-based models				
1-day	LFM= 124 + 135 EVI_1	0.15	0.00	<0.001
8-day	LFM= 91.1 + 171 EVI_8 + 78.4 NDVI_8	0.20	0.15	<0.001
16-day	**LFM=2.1 + 402 EVI2_16 + 144 NDVI_16**	**0.46**	**0.40**	**<0.001**
WIMS-based models				
NFDRS	LFM = 78.7 + 0.807 NFDRS	0.37	0.33	<0.001
KBDI	LFM = 191 - 0.0624 KBDI	0.06	0.01	0.050
Hybrid models				
1-day	LFM = 101 + 67.6 EVI_1 + 0.654 NFDRS - 0.0652 KBDI	0.46	0.37	<0.001
8-day	**LFM = 91.2 + 7.77 EVI_8 + 0.735 NFDRS - 0.0524 KBDI**	**0.49**	**0.41**	**<0.001**
16-day	LFM = 35.2 + 0.650 NFDRS + 244 EVI_16	0.38	0.30	<0.001

Table 6. Models predicting *in situ* dead fuel moisture. MODIS-based models were generated from remotely sensed Terra-MODIS daily, 8-day composites, and 16-day vegetation index data. WIMS-based models are calculated from onsite weather data. Hybrid models were developed using the best predictors from both MODIS and WIMS-based models. Bold font indicates the strongest and recommended model.

	Model	R^2	**Pred** R^2	P
MODIS-based models				
1-day	DFM = 16.0 + 8.61 EVI_1	0.00	0.00	0.082
8-day	DFM = 10.5 + 16.7 EVI_8 + NDVI_8	0.14	0.06	0.001
16-day	**DFM = 5.55 + 39.3 EVI2_16 + 10.9 NDVI_16**	**0.19**	**0.12**	**0.002**
WIMS-based models				
NFDRS	DFM = 7.62 + 1.12 NFDRS	0.05	0.00	0.066
KBDI	DFM = 19.9 - 0.00355 KBDI	0.01	0.00	0.477
Hybrid models				
1-day	DFM = 8.53 + 4.93 EVI_1 - 0.00807 KBDI + 1.11 NFDRS	0.13	0.00	0.116
8-day	DFM = 4.34 + 20.8 EVI_8 + 0.945 NFDRS	0.14	0.00	0.010
16-day	DFM = 0.79 + 56.2 EVI2_16 + 0.577 NFDRS	0.19	0.00	0.026

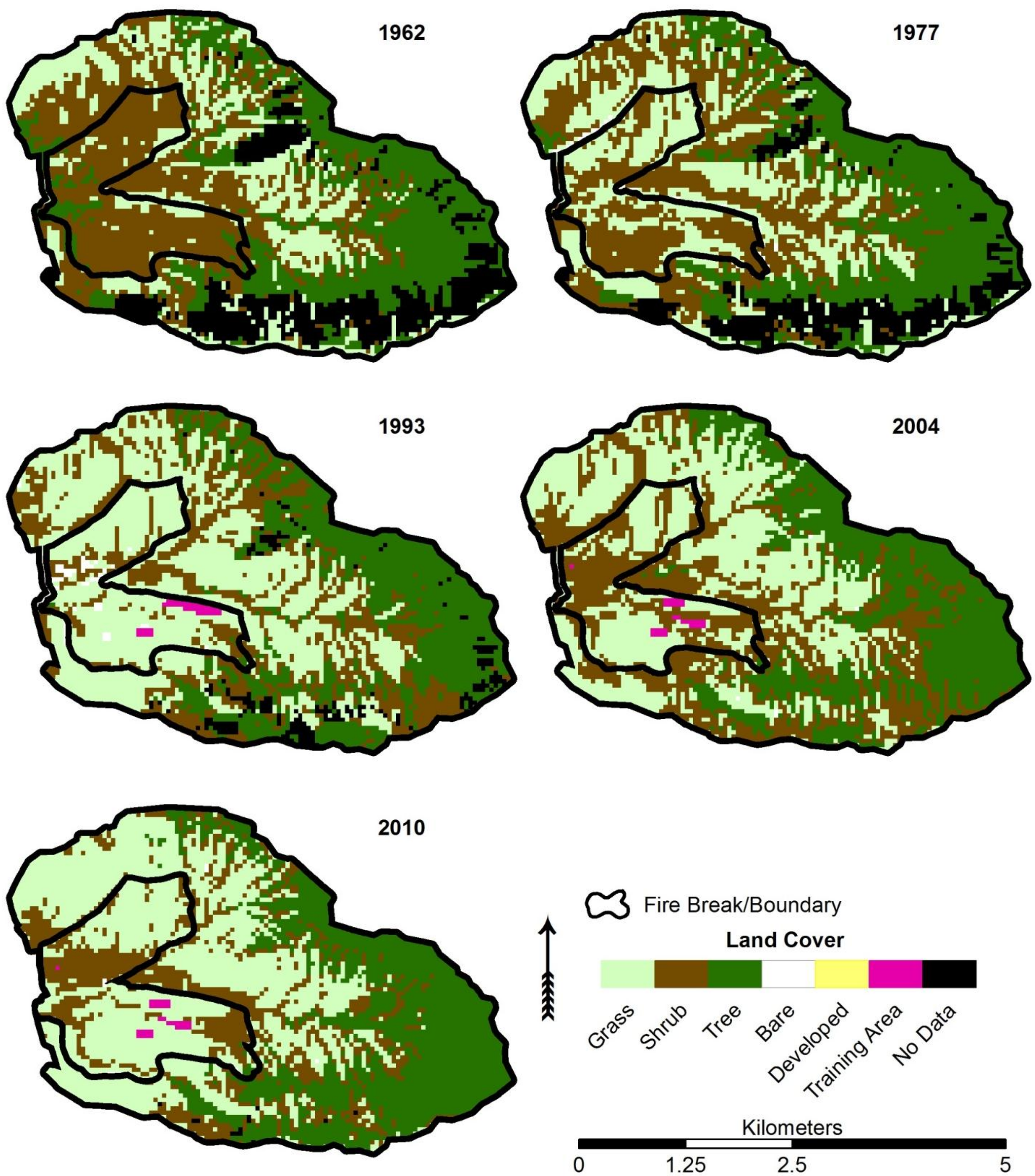

Figure 1. Land cover at Makua Military Reservation on leeward Oahu, Hawaii from 1962 through 2010. The area inside the firebreak is heavily utilized for military training activities, and fire is frequent. The area outside the firebreak has historically been forested, has many threatened and endangered species, and is impacted to a lesser extent by military activities and fire.

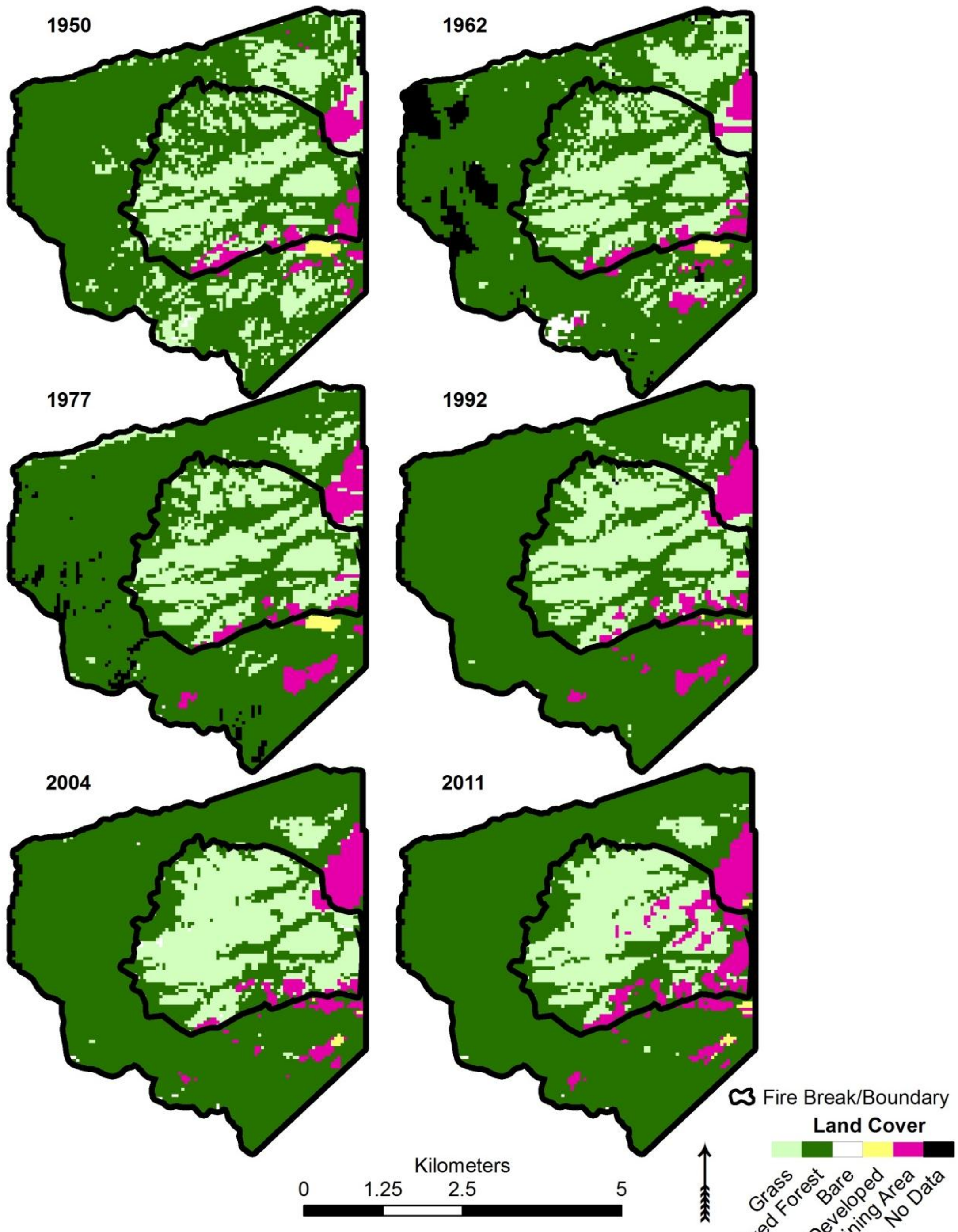

Figure 2. Land cover at Schofield Barracks on leeward Oahu, Hawaii from 1950 through 2011. The area inside the firebreak is heavily utilized for military training activities, and fire is frequent. The area outside the firebreak is maintained for woody species, and is less affected by military activity and fire.

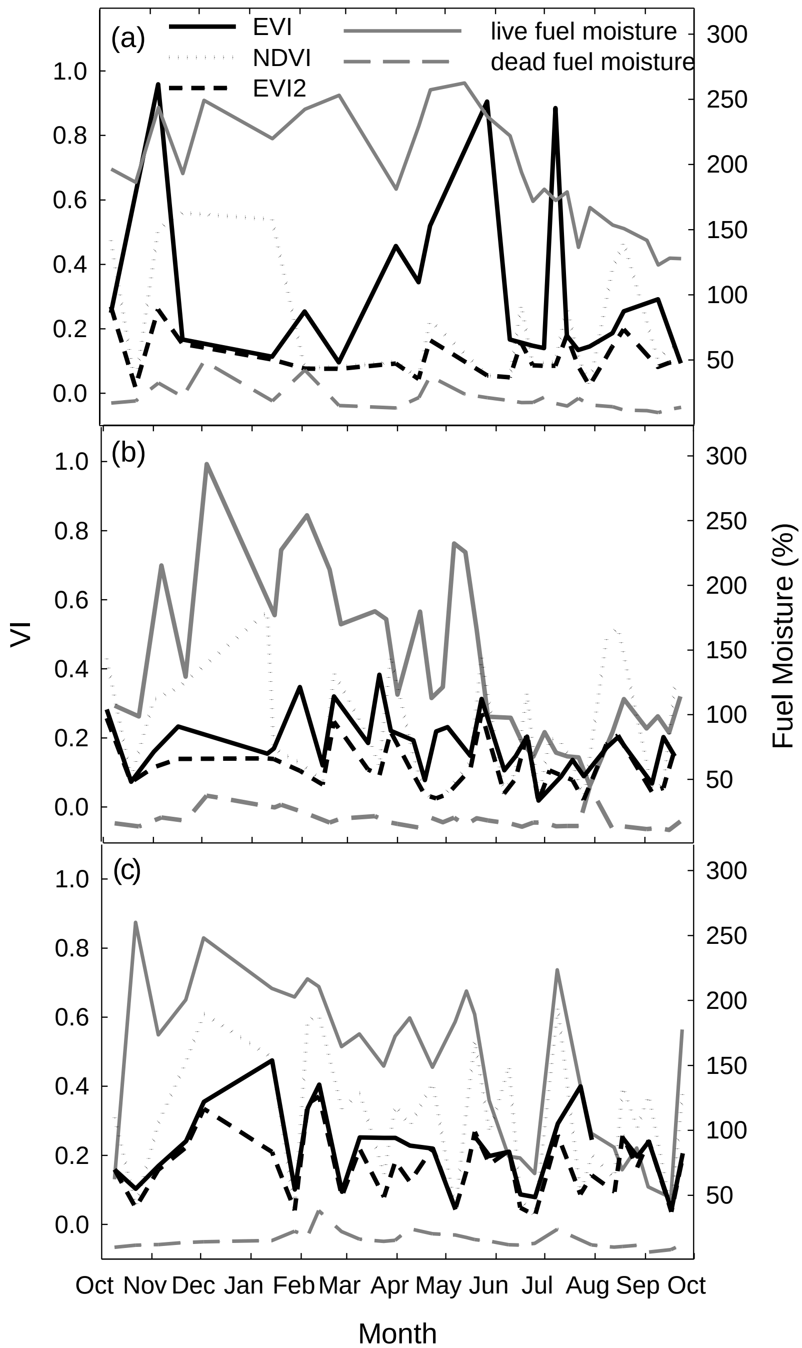

Figure 3: Temporal trends of *in situ* live and dead fuel moisture and daily MODIS-derived vegetation indices (VI) for nonnative invasive guinea grass ecosystems at (*a*) Schofield Barracks, (*b*) Dillingham Ranch, and (*c*) Yokohama State Park on Oahu, Hawaii from October 2009 – October 2010. VI's (NDVI, EVI, and EVI2) are shown by black lines, and live (solid) and dead (dashed) fuel moisture is shown in grey.

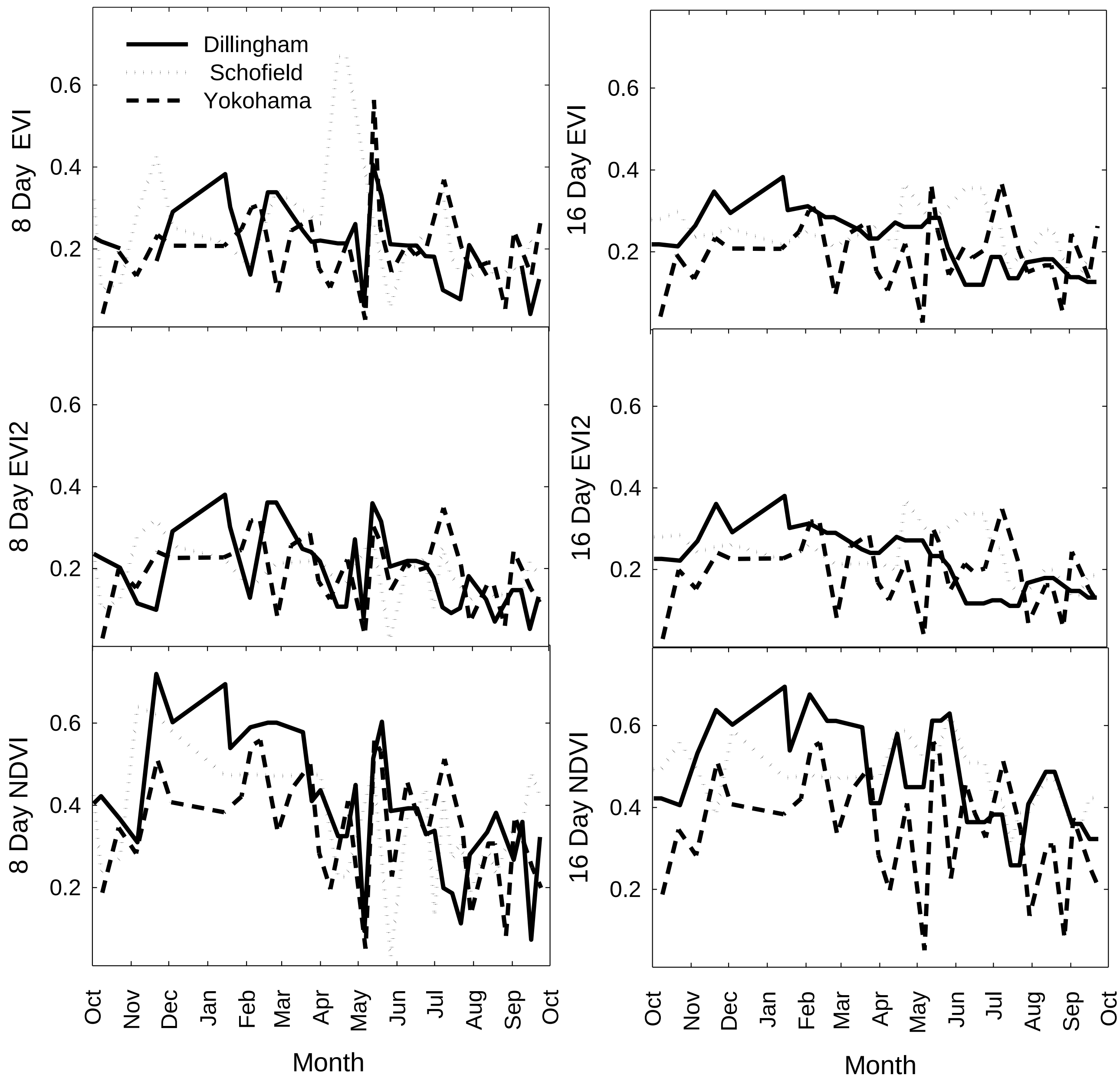

Figure 4: Temporal trends in 8-day composite and 16-day MODIS-derived vegetation indices (VI) for nonnative invasive guinea grass ecosystems at Schofield Barracks, Dillingham Ranch, and Yokohama State Park on Oahu, Hawaii from October 2009 – October 2010.

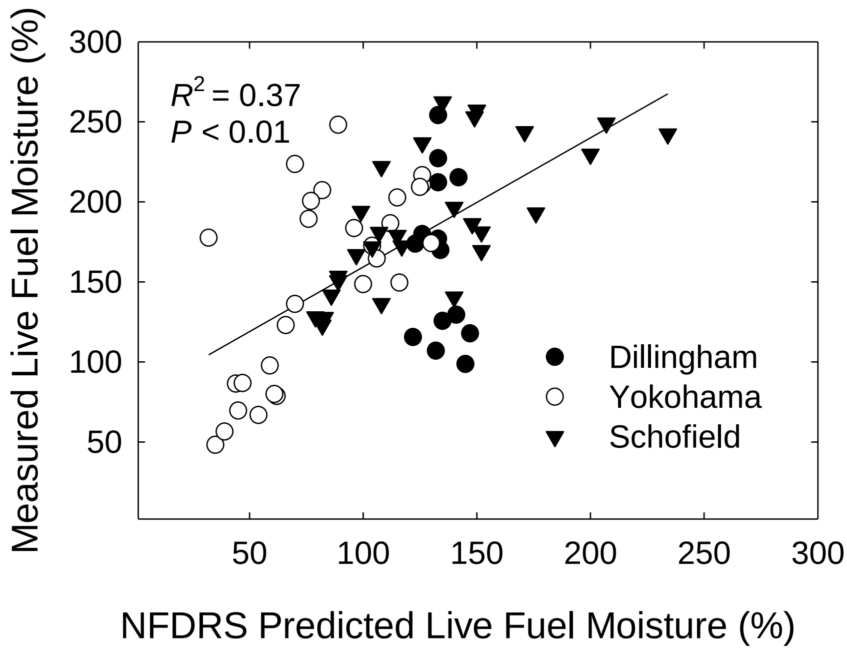

Figure 5: NFDRS system of live fuel moisture prediction (x-axis) vs. *in situ* live fuel moisture (y-axis) measurements.

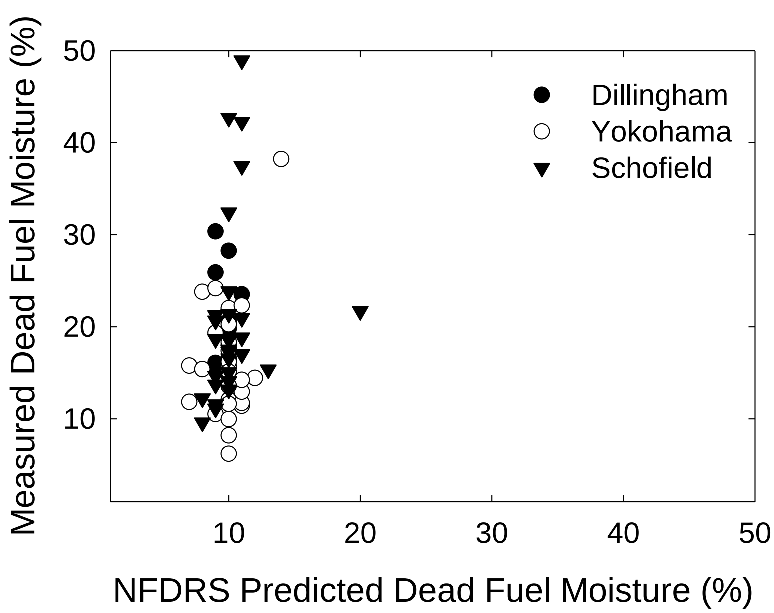

Figure 6: NFDRS system of dead fuel moisture prediction (x-axis) vs. *in situ* dead fuel moisture (y-axis) measurements.

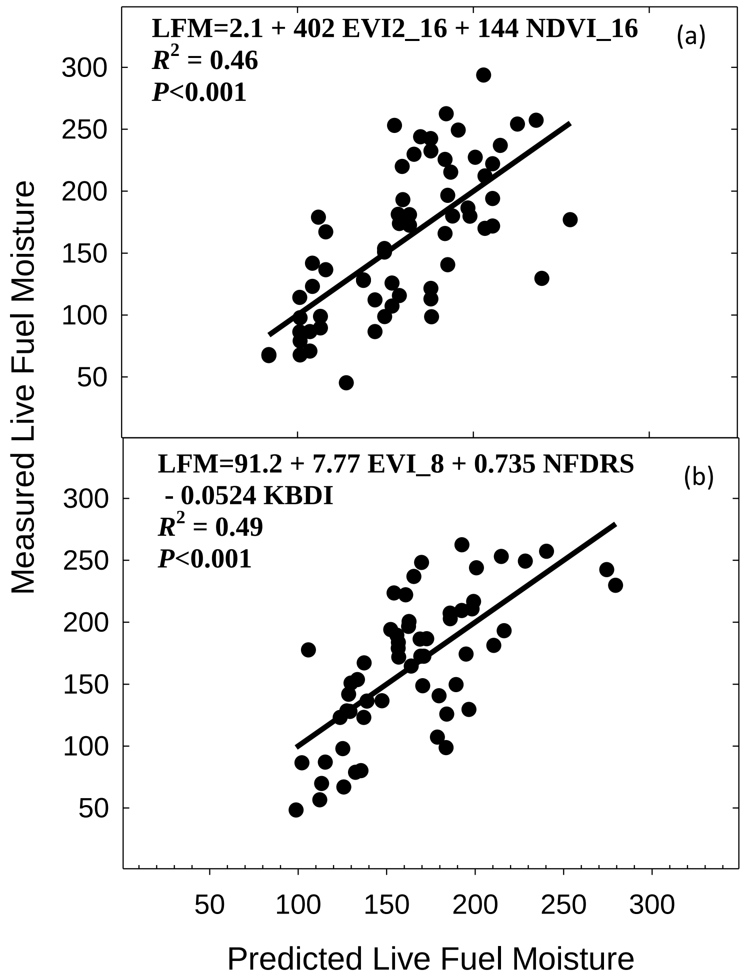

Figure 7: Live fuel moisture prediction (x-axis) using a) MODIS vegetation index and b) Hybrid models vs. *in situ* live fuel moisture (y-axis) measurements.

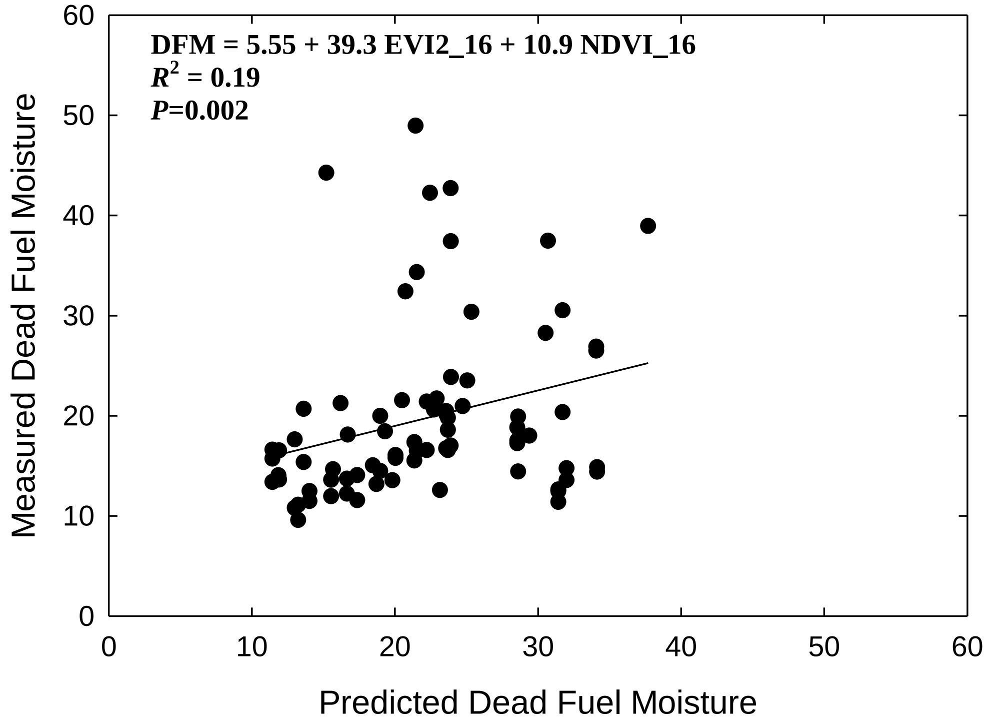

Figure 8: Dead fuel moisture prediction (x-axis) using MODIS vegetation indices vs. *in situ* live fuel moisture (y-axis) measurements.

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Deliverables crosswalk table

Proposed	Delivered	Status
Conference Presentations	*(i)* Hawaii Ecosystems Meeting*: Predicting and Managing Fire in Oahu's Nonnative Grasslands* *(ii)* Hawaii Conservation Conference: *Changes in land cover and fire risk associated with nonnative grass invasion in Hawaii* *(iii)* Ecological Society of America: *Changes in land cover and fire risk associated with nonnative grass invasion in Hawaii* *(iv)* 5th International Fire Ecology and Management Congress: *Improved prediction of fuel moisture in invasive guinea grasslands in Hawaii using MODIS data*	Presented July 2011 Presented July 2012 Presented August 2012 Presented December 2012
Computer model/algorithm	Algorithm with protocol for use of new methodology	Protocol and algorithm developed; Work in progress with the Pacific Fire Exchange to develop user friendly web tools to access this algorithm
Dissertation Chapter(s)	*(i) Changes in land cover and fire behavior associated with nonnative grass invasion in Hawaii* *(ii) Improved prediction of live and dead fuel moisture in invasive* Megathyrsus maximus *grasslands in Hawaii with Moderate Resolution Imaging Spectroradiometer (MODIS)*	Dissertation Completed 12/15/12
Refereed Publication(s)	*(i) Changes in land cover and fire behavior associated with nonnative grass invasion on a tropical island* *(ii) Improved prediction of live and dead fuel moisture in invasive Megathyrsus maximus grasslands in Hawaii with Moderate Resolution Imaging Spectroradiometer (MODIS)*	In *review*, Forest Ecology and Management In prep for Remote Sensing of Environment
Final Report	Final Report submitted to JFSP	Submitted to JFSP