IMPROVED WILDFIRE MANAGEMENT IN *MEGATHYRSUS MAXIMUS* DOMINATED ECOSYSTEMS IN HAWAIʻI

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For Miles and Leo

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ABSTRACT

Wildfire management in Hawaii is complicated by the synergistic influences of nonnative invasive grasses and increased human ignitions. The frequent, high severity fires that often result threaten surrounding ecosystems and developed areas. The overarching goal of this research was to improve wildfire management in guinea grass (*Megathyrsus maximus*) dominated ecosystems in Hawaii using *in situ* fuels data collection, fire behavior modeling, remote sensing, and ecological restoration. Specific objectives included: *i)* quantification of rates of land cover conversion at the grass/forest ecotone from 1950-2011; *ii)* an accurate assessment of the spatial and temporal variability in guinea grass fuels; *iii)* use of *in situ* fuels data to parameterize a custom fuel model for guinea grass dominated ecosystems; *iv*) use of MODIS-based vegetation index data to accurately predict real-time fuel moisture content; and *v)* assessment of whether native species restoration can simultaneously compete with guinea grass and decrease fire potential.

The results of this research provide tools to better predict and manage wildfire. The historical analysis showed that type conversion associated with grass invasion and subsequent fire occurred widely prior to active fire management, and that predicted rates of fire spread are 3-5 times higher in grasslands than in forests. Guinea grass total fine fuel loads ranged widely, from 3.26 to 34.29 Mg ha^{-1}, highlighting the importance of real-time, site-specific data for fire management. Field data were used to parameterize a custom fuels model, which better predicted fire behavior than national standard or previous custom fuel models for guinea grass. MODIS-based models better predicted live fuel moisture (R^2=0.46) than the currently used National Fire Danger Rating System (R^2=0.37) , providing managers with an improved method for assessing this critical component of fire behavior. Native outplant survival averaged 51% twenty-seven months after planting, and outplant treatments successfully suppressed guinea grass (P<0.001). Predicted fire behavior in outplant and untreated control plots, however, did not differ, likely due to the low moisture content of *D. viscosa* which dominated the restoration trails. Together, this research provides the foundation for improved fire management in guinea grass ecosystems in Hawaii, and can inform similar work throughout the tropics.

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CHAPTER 1. INTRODUCTION

Fire regimes are being impacted globally by anthropogenic alterations such as land use change, increased urbanization, invasive species, and climate change (D'Antonio and Vitousek, 1992; Bowman et al., 2011; Bradshaw, 2012; Taylor and Scholl, 2012). A familiar example of these impacts is the well-publicized large, high-intensity wildfires in shrub and forest ecosystems of the U.S. West. Synergies between decades of fire suppression, increased wildland-urban interface, and climate change are resulting in fires of higher intensity and severity than those recorded historically (Veblen et al., 2000; Keeley, 2006; Littell et al., 2009).

Somewhat less publicized, but equally detrimental ecologically, are the impacts that altered fire regimes have had on temperate grassland ecosystems. In fire dependent eastern North American tallgrass prairies, invasive grasses with high fuel moistures can lengthen fire return intervals and reduce fire size in an ecological system that evolved with frequent and large fires (McGranahan et al., 2012). Conversely, in the Great Basin, Mojave and Sonoran deserts of western North America, invasive grasses can drastically decrease the mean fire return interval by providing a continuous, highly flammable fuelbed, which often converts shrubland ecosystems to invasive grasslands (Mack and D'Antonio, 1998; Brooks and Pyke, 2002).

In tropical ecosystems, large expanses of forests have been cleared for agriculture and pasturelands, reducing forest cover and facilitating nonnative grass dominance (Kauffman et al., 2003; Raghubanshi and Tripathi, 2009; Veldman and Putz, 2011; Bradshaw, 2012). A cycle of positive feedbacks between nonnative invasive grasses and repeated wildfire is now a reality in many tropical landscapes formerly occupied by native woody vegetation (D'Antonio and Vitousek, 1992; Mack and D'Antonio, 1998; Williams and Baruch, 2000; Wilcox et al., 2012). The synergistic interactions of fire and invasive grasses now pose serious threats to the biological integrity and sustainability of these ecosystems (LaRosa et al., 2008; Wolfe and Van Bloem, 2012).

Several highly flammable African pasture grasses were introduced to Hawaii for livestock forage and as ornamentals in the late 1800’s and early 1900’s (Williams and Baruch, 2000; Motooka et al., 2003). In addition to impacting fire regimes, these invasive grasses typically outcompete native plants for above- and belowground resources (Ammondt and Litton, 2012; Ammondt et al., 2012), and can 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 also typically form a continuous understory of fine fuels, even under a full forest canopy (LaRosa et al., 2008), thereby increasing the potential for future fire and type conversion to nonnative grassland. Once a fire does occur, the postfire plant community is typically dominated by rapid grass regeneration, which then predisposes these ecosystems to more frequent and higher intensity fires as a result of increased surface fine fuel loads and altered microclimate (Smith and Tunison, 1992; Pyne et al., 1996; Blackmore and Vitousek, 2000; LaRosa et al., 2008; Ainsworth and Kauffman, 2010).

Guinea grass (*Megathyrsus maximus,* [Jacq.] previously *Panicum maximum* and *Urochloa maxima* [Jacq.]), was introduced to Hawaii for cattle forage and became naturalized in the islands by 1871 (Motooka et al., 2003; Portela et al., 2009). It quickly became a problematic invader in Hawaiian landscapes because it is adapted to a wide range of ecosystems (*e.g*., dry to mesic), where it alters flammability by dramatically increasing fuel loads and continuity. Year-round high fine fuel loads with a dense layer of standing and fallen dead biomass maintain a significant fire risk throughout the year. Because guinea grass recovers quickly following disturbance, including fire, and is competitively superior to most native species (Ammondt and Litton, 2012), many areas of Hawaii, as well as throughout the tropics, are now dominated by this nonnative invasive grass (Beavers, 2001).

Tropical dry forests are among the most threatened ecosystem types in the world (Murphy and Lugo, 1986), and the widespread invasion of nonnative grasses and change in fire regimes are driving factors in their decline. In order to preserve remnants of these forests and to restore degraded dryland ecosystems, the invasive grass/wildfire cycle (D'Antonio andVitousek, 1992) must be managed, and ultimately eliminated. The overarching objective of this dissertation research was to investigate tools to improve wildfire prediction in guinea grasslands of Oahu, Hawaii using *in situ* fuels data collection, fire behavior modeling, remote sensing, and ecological restoration with native woody species. Because guinea grass, along with similar large tropical grasses, is a widespread invader in the tropics (Williams and Baruch, 2000), this research can inform fire management efforts throughout the tropics.

In a landscape analysis of land cover change from 1950-2011 (Chapter 2), field data and modeling were used to compare fuels and potential fire behavior in adjacent forests and grasslands. The rate and extent of land cover change at the grassland-forest boundary in and around two heavily utilized areas at Schofield Barracks and Makua Military Reservation on Oahu, Hawaii was then quantified. I hypothesized that (*i*) fine fuel loads and heights would be lower and fuel moisture higher in forest plots compared to grass plots due to altered microclimate in the understory (Hoffmann et al., 2002) and shading in forest plots (Funk and McDaniel, 2010); (*ii*) as a result of different fuel properties (*i.e.* 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 compared to grass plots (Freifelder et al., 1998); and (*iii*) rates of conversion from forest to grassland would increase through time over the past 50+ years due to increased ignition sources, and that rates of conversion would be higher in heavily utilized grassland areas than in adjacent forests (Beavers, 2001). To test these hypotheses, I measured fuel loads in forest and grassland plots, and used these data to model potential fire behavior. Land cover change was quantified from 1950-2011 with historical imagery. Results from this study suggest that type conversion associated with nonnative grass invasion and subsequent fire occurred widely prior to active management, and that once converted to grasslands there is a significant increase in the spread and intensity of modeled fires. However, slower conversion rates in recent years suggest that active fire management is currently preventing further degradation of existing forests.

I then assessed the spatial and temporal variability in guinea grass fuels (live and dead fuel loads and moistures) on high fire risk areas on the Waianae Coast and North Shore of Oahu, Hawaii (Chapter 3). Specific objectives included quantifying the: (*i*) spatial variability in live and dead fine fuel loads in guinea grass ecosystems in high fire risk areas; (*ii*) temporal variability at multiple scales (interannual, intraannual, and fine-scale) in fuel loads and fuel moistures in guinea grass ecosystems in high fire risk areas; and (*iii*) relationship between weather variables (precipitation, relative humidity, wind speed, and temperature) and fine fuel loads and moistures to explore predictive capacity to inform fire management of guinea grass ecosystems in Hawaii. Overall, fine fuel loads and moisture content exhibited tremendous variation, both spatially and temporally, highlighting the importance of real-time, site-specific data for fire prevention and management. However, tight correlations with commonly quantified weather variables demonstrate the capacity to accurately predict fuel variables across large landscapes to better inform management and research on fire potential in guinea grass ecosystems in Hawaii, and throughout the tropics.

Using field data, a custom fuel model was created to predict the spread of fire through guinea grass dominated ecosystems (Chapter 4). I hypothesized that a fuel model based on *in situ* field fuels measurements and climate data would perform better than either national tall grass fuel models (Anderson, 1982; Scott and Burgan, 2005) or previous custom models for this species in Hawaii (Beavers, 2001). To test this hypothesis, I used field data collected in guinea grass dominated ecosystems on the Waianae Coast and North Shore areas of Oahu, Hawaii to develop a custom guinea grass fuels model. This custom model, as well as multiple standard tall grass and previous custom fuel models, were tested using data from 5 prescribed fires in guinea grass dominated ecosystems (Beavers, 2001). Of all fuel models tested, my custom model output best matched fire behavior observed in validation fires, suggesting that a field based fuel model can improve the accuracy of fire behavior modeling, thereby increasing capacity for land managers to make predictions of fire behavior in *M. maximus* ecosystems in Hawaii and throughout the tropics.

Fuel moisture content is an important parameter driving fire behavior and spread. It is relatively easy to quantify *in situ*, but time consuming and very variable temporally, making it difficult to predict. I explored alternative methods for real time fuel moisture prediction using MODIS-based remotely sensed vegetation indices (Chapter 5). Specific hypotheses tested included: *(i)* because vegetation indices are a good indicator of vegetation greenness, there would be strong relationships between vegetation indices derived from MODIS imagery and *in situ* live fuel moisture content. While I expected stronger relationships between vegetation indices and live fuel moisture, I also expected to see weaker correlations with dead fuel moisture, as moisture change in both fuel components often occur simultaneously; *(ii)* because the Enhanced Vegetation Index (EVI) performs well in areas of high biomass (Jensen, 2007), it would be a better predictor of fuel moisture than other vegetation indices given the dense grass cover present on the study sites; *(iii)* daily MODIS data would be a better predictor of *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 pulse precipitation events. MODIS-based predictive models for live fuel moisture were only moderately effective (R^2= 0.46), but outperformed both 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 the Enhanced Vegetation Index 2 (EVI2) and the Normalized Difference Vegetation Index (NDVI) (R^2= 0.19). These improvements in fuel moisture prediction in nonnative grasslands can greatly improve management of fire in Hawaii, as well as inform fire management in other grass-dominated tropical ecosystems.

Finally, the potential for using native woody species in restoration outplant treatments to simultaneously compete with guinea grass and reduce fire occurrence and spread was investigated (Chapter 6). I quantified species cover and fuel loads 27 months after outplanting, and modeled fire behavior in a randomized complete block design (three native species outplant treatments, herbicide control and untreated control) in a lowland dry ecosystem dominated by guinea grass. Specific hypotheses tested included: (*i)* guinea grass cover and fine fuel loads would be lower in native outplant treatment plots than in herbicide control or untreated control plots due to competition between the grass and native plants (Ammondt and Litton, 2012); (*ii)* total fuel loads would be highest in untreated control plots due to chemical grass suppression in outplant and herbicide control treatments (Motooka et al., 2002); (*iii)* fine fuel moisture content would be higher in outplant treatments than in either herbicide control or untreated control plots due to shading by woody species (Bigelow and North, 2012); and (*iv*) outplanting native species would result in decreased potential fire spread and intensity compared to untreated control plots (Griscom and Ashton, 2011; Bigelow and North, 2012). Native species survival was moderate (51%) 27 months after outplanting, and outplanting treatments successfully reduced guinea grass live and dead grass fuel loads by more than 92%

($P<0.001$) and 68% ($P<0.05$), respectively. However, there was no concurrent reduction in potential fire behavior parameters. This was likely due to the very low live moisture content (84%) of the dominant *D. viscosa* individuals in every outplanting plot, which was substantially lower than that of other native woody species (201-328%). These results demonstrate that restoring a native species component to degraded tropical dry forest sites is possible, but that species selection is critical when fire management is a primary goal, and successful ecological restoration with native species does not always alter the potential for fire and subsequent site degradation.

Together, the research presented in this dissertation provides the foundation for improved fire management in guinea grass ecosystems in Hawaii, and can inform similar work in grasslands throughout the tropics. An accurate assessment of the current variability in guinea grass fuel loads as well as a quantification of the historical rates of conversion at the grass/forest ecotone provide a foundation to further investigate approaches for future fire prediction, fuels management, and potential for dry forest restoration. Because tropical dry ecosystems worldwide are rapidly being degraded due to invasive species, altered fire regimes, and expanding human populations, it is imperative that continued measures be taken to protect and preserve these imperiled ecosystems.

CHAPTER 2. CHANGES IN LAND COVER AND FIRE BEHAVIOR ASSOCIATED WITH NONNATIVE GRASS INVASION IN HAWAII

Abstract

It is generally accepted that nonnative grass invasion and subsequent fire result in landscape scale type conversion from forest to grassland throughout the tropics. However, there is little published data to support this paradigm on tropical islands, and no study has examined changes in fire potential following type conversion in these systems. My objectives were to: (*i*) compare potential fire behavior in forests vs. grasslands, and (*ii*) measure land cover change from 1950-2011 along two grassland/forest ecotones in Hawaii. I quantified fuel loads and moistures in nonnative forest and grassland (*Megathyrsus maximus*) plots (n=6), and modeled potential fire behavior with BehavePlus. Land cover change was then quantified from 1950-2011 with historical imagery. Fine fuel loads and moisture content did not differ between cover types, but mean surface fuel height was 31% lower in forests than grasslands (P<0.02). Predicted rates of spread were 3-5x 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 2-3x higher in grasslands (2.8-10.0 m) than forests (0-4.3 m) (P<0.01). Rapid conversion from forest to grassland occurred for ~40 years prior to implementation of active fire management in the early 1990's. These results support general paradigms for the wider tropics, and demonstrate that type conversion associated with nonnative grass invasion and subsequent fire occurs widely on tropical islands without active management. Moreover, once converted to grassland there is a significant increase in fire intensity, likely providing a positive feedback to continued grassland occurrence in the absence of active fire management.

Introduction

It is generally well accepted that the synergistic effects of nonnative grass invasion and repeated wildfire can detrimentally impact native species (Loope, 1998; Loope, 2004; Hughes and Denslow, 2005), often converting woody plant communities into nonnative grasslands (Hughes et al., 1991; D'Antonio and Vitousek, 1992; Eva and Lambin, 2000;

Hoffmann et al., 2002; Ainsworth and Kauffman, 2010). In Hawaii, grass invasion and increased fire frequency is particularly problematic, as fire is not believed to have historically played a large role in the evolution of these island ecosystems (LaRosa et al., 2008), and many native species do not possess adaptations to survive a regime of frequent fires (Rowe, 1983; Vitousek, 1992) or to passively recover following fire (D'Antonio et al., 2011). While prior studies have examined grass-fire interactions at the plot level (Hughes et al., 1991; Ainsworth and Kauffman, 2010), no study in Hawaii has quantified this type conversion over large spatial extents or long temporal scales. One recent study in Hawaiian tropical dry forests showed that at the plot level, invasive grasses remain dominant, with little native recovery, up to 37 years after fire and conversion of forest to nonnative grassland (D'Antonio et al., 2011).

Invasive grasses can alter the occurrence and behavior of fires via a variety of both intrinsic (characteristics of the plants themselves) and extrinsic (arrangement of plants across the landscape) fuel properties (Brooks et al., 2004). Intrinsic fuel properties associated with type conversion from forest to grassland can include increased flammability due to lower fuel moisture (Brooks et al., 2004) and competitive superiority in the postfire environment (Veldman and Putz, 2011). Extrinsic properties, in turn, can include increased horizontal fuel continuity (Brooks et al., 2004), changes in microclimate (Blackmore and Vitousek, 2000; Hoffmann et al., 2002), high fine fuel loads (Litton et al., 2006) , and alterations to packing ratios (Brooks et al., 2004; Hoffmann et al., 2004).

Highly flammable African pasture grasses were introduced to Hawaii for livestock forage and as ornamentals in the late 1800’s and early 1900’s (Williams and Baruch, 2000; Motooka et al., 2003). 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 often form a continuous understory 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 dominated by rapid grass regeneration, which then is thought to predispose these ecosystems to more frequent and higher intensity fires as a result of increased surface 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 reinvasion is a common occurrence in tropical ecosystems globally following land cover change (D'Antonio and Vitousek, 1992).

Throughout the tropics, conversion from forest to grassland has resulted in increased cover of invasive grasses (Williams and Baruch, 2000). Guinea grass (*Megathyrsus maximus,* [Jacq.] previously *Panicum maximum* and *Urochloa maxima* [Jacq.]), was introduced to Hawaii for cattle forage and became naturalized in the islands by 1871 (Motooka et al., 2003; Portela et al., 2009). It quickly became a problematic invader in Hawaiian landscapes because it is adapted to a wide range of ecosystems (*e.g*., dry to mesic), where it alters flammability by dramatically increasing fuel loads and fuel continuity. Year-round high fine fuel loads with a dense layer of standing and fallen dead biomass maintain a significant fire risk throughout the year in guinea grass dominated ecosystems in Hawaii (Chapter 3). Because guinea grass recovers quickly following disturbance (*i.e.* fire, ungulate grazing, land use change, etc.) and is competitively superior to native species (Ammondt and Litton, 2012), many areas of Hawaii, as well as throughout the tropics, are now dominated by this nonnative invasive grass (Chapter 3).

Plot level studies provide important insights into the relationships between nonnative invasive grasses, fire, and type conversions, but a greater understanding of the mosaic created by grass invasion, fire, and postfire succession is 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 long 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 across the tropics is that fire shifts composition from woody communities to 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 adjacent forests. However, few studies have looked at the landscape vegetation cover patterns resulting from repeated fire and grass invasion at larger scales (Blackmore and Vitousek, 2000; Grigulis et al., 2005).

The objectives of this study were to: (*i*) use field data and modeling to compare fuels and potential fire behavior in adjacent forests and grasslands, and (*ii*) measure the rate and extent of land cover change at the grassland-forest boundary from 1950-2011 in and around two heavily utilized areas at Schofield Barracks and Makua Military Reservation on Oahu, Hawaii. I hypothesized that (*i*) fine fuel loads and heights would be lower and fuel moisture higher in forest plots compared to grass plots due to altered microclimate in the understory (Hoffmann et al., 2002) and shading in forest plots (Funk and McDaniel, 2010); (*ii*) as a result of differences in fuel properties (*i.e.* 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 compared to 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 (*iv*) rates of conversion would be higher in heavily utilized grassland areas than in adjacent forests (Beavers, 2001). To test these hypotheses, I measured fuel loads and moisture in forest and grassland plots, and used these data to model potential fire behavior. Land cover change was quantified from 1950-2011 with historical imagery.

Methods

Fuel Quantification

Fuel loads in nonnative-dominated guinea grass ecosystems in areas of open grassland (grass sites) vs. areas with a nonnative tree overstory (forest sites) were quantified in the summer of 2008. Sites were located in the Waianae Kai Forest Reserve (forest: elevation, 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; (Giambelluca et al., 2011); T. Giambelluca, *unpub. data*) on the Waianae Coast and North Shore areas, respectively, of Oahu, Hawaii (Figure 1). 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* (Humb. andBonpl. ex Willd.) Kunth) and silk oak (*Grevillea robusta* A. Cunn. ex R. Br.) 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 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. Sites were chosen randomly among all possible locations that met these selection 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 and (*iv*) fuel moisture (for both live and dead fine fuels). In each plot, three parallel 50m transects were established 25m apart, and all herbaceous fuels were destructively harvested in six 25 x 50 cm sub-plots at fixed locations along each transect (n=18/plot). Samples were immediately placed into 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.

Additionally, live standing trees and standing and downed dead wood were quantified in each plot. The diameter at 1.3m height (dbh) of all *L. leucocephala* trees that occurred in 1 x 50 m belt transects was measured. Biomass was determined using an existing allometric equation (Dudley and Fownes, 1992) after first testing its utility for estimating biomass for trees from the Waianae Kai field site across the widest possible range of sizes found (n=20, dbh ranging from 1.5 to 6.2 cm dbh). There was a strong correlation between predicted and observed values (r^2= 0.95), indicating that the existing equation accurately estimates *L. leucocephala* biomass for this study site. 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 fuel height was recorded as 70% of the average maximum height across subplots (Burgan and Rothermel, 1984).

Fire Modeling

The fine fuel data described above were used to parameterize the BehavePlus 5 Fire Modeling System (Andrews et al., 2005) to generate predicted fire behavior estimates for each plot. Live and dead fuel heat contents were measured by bomb calorimetry (Hazen Research, Inc., Golden, CO, USA). Previously published values for 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) using a LI-3100C Area Meter (LI-COR Environmental, Lincoln, Nebraska) and water displacement. After examining wind speed data collected at the field sites, I selected an average 20-ft windspeed (15 km hr^{-1}) and an extreme 20-ft windspeed (30 km hr^{-1}) to simulate moderate and severe wind scenarios for 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-ft wind speed) to 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 determined from 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). Classifications for Makua were derived from images for five time periods: 1962, 1977, 1993, and 2004 aerial photographs, and

2010 Worldview-2 scenes. Schofield classifications 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 georegistered to the 2004 images with a first-order polynomial warping 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 I have defined these areas as predominantly forest or grass, respectively, each contains patches of both grass and woody cover as well as patches of more intensive utilization (*i.e.* military training areas, developed). ArcGIS Data Management tool *Create Fishnet* was used to divide the study sites into grids with a 50 x 50 m cell size and then to clip the grids to the site boundaries. After the grids were created, they were overlaid onto the images for classification.

Land cover in 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. Therefore, at Schofield 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.

Examination of historical imagery showed an apparent pattern of increasing homogeneity over time. Therefore, I used Fragstats, a spatial pattern analysis program

(McGarigal et al., 2012), to quantify landscape metrics for each date at each AOI. Metrics examined included number of patches, contagion (the tendency of patches to occur in large, continuous patches, expressed as a percentage, where zero is maximally heterogeneous), and perimeter: area ratio.

Statistical Analyses

General linear models were used to determine 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. Because there is an elevation/ precipitation gradient at Waianae Kai Forest Reserve, and forest plots were clustered ~150 m higher than grassland plots, MAP was also 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 for ease of interpretation. Minitab v. 15 (Minitab, Inc., State College, PA) was used for all statistical analyses, and significance was assessed at α=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.

Results

Fuel Quantification

After controlling for differences in MAP (P<0.01), there were few differences in fine fuel loads between forests and grasslands, 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 an effective predictor of both live (P=0.02) and dead (P=0.05) fuel moisture, and there was no evidence of differences in fuel moisture between forest and grassland (live, P=0.19; dead, P=0.95). Live fine fuel moisture at the time of measurement 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 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), modeled rate of spread was 3-5x higher in grassland (5.0 to 17.7 m min^{-1}) than forest (0 to 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) plots ($P<0.01$); 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 ($P=0.27$) or extreme ($P=0.27$) wind conditions (Table 2).

Historical and Spatial Land Cover Change Analysis

Invasive grassland cover increased in grass areas (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 2-5). At Makua, conversion from forest to grassland in the surrounding forest area (1244 ha area) was slower (1.78 ha yr^{-1}) than in the grass area (Figure 2). In the forest area at Schofield (1576 ha), unlike Makua, conversion of grassland to forest occurred at a faster rate (4.75 ha yr^{-1}) than in grass areas (Figure 3). Change in land cover over time was more dynamic at Makua (Figure 3) than at Schofield (Figure 4), coinciding with large and frequent fires at Makua, and fewer acres burned at Schofield.

The number of patches decreased steadily in forest areas at both Schofield and Makua from 1950 until 1992/1993, and then increased again in 2004 and 2010/2011. The number of patches in grass areas fluctuated over time, without any clear trends (Figure 6a). Contagion in forested AOI's differed greatly by site. At Schofield, contagion was >50% for all dates, and reached >80% by 2004. At Makua, contagion also gradually increased, but remained much lower (29-49%) than that observed at Schofield. In the heavily utilized grass area, contagion was similar at both sites, ranging from 43-59%, and stayed fairly constant over time. The perimeter:area ratio varied greatly over the sample period, with no clear trends over time or site (Figure 6c).

Discussion

These results show that the areas studied have experienced large type conversions from forest to grassland over the past 50+ years, and that this conversion to grasslands has subsequently altered fuel heights and increased modeled fire spread and intensity. As hypothesized, increased fuel bed depth and a differential 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 plot-level 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 the synergistic effects of fire and nonnative grass invasion can lead to a pervasive 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, I expected to see an increase in the rate and extent of conversion in more recent years as compared to historical landscapes. While I 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, I 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, 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 moistures, remoteness, intensity of military training, and common anthropogenic ignitions (*i.e.* arson, roadside). In 2004, all live fire training stopped at Makua to address cultural and fire concerns at this site, but several human ignited fires have occurred since.

At Schofield, however, the pattern of change over time in the forest was very different from Makua. Grass cover steadily decreased from 1950 to present, while woody species, and to a lesser extent military training areas, increased. While this area is inaccessible due to unexploded ordinance, I 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 (Chapter 3). Additionally, fire managers at Schofield have been quite 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 installation, and a well-designed fire management plan appears to have largely limited severe wildfires (Beavers and Burgan, 2001).

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 believed by many in the science and management communities in the state. 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).

In summary, I investigated evidence for the dominant paradigm that grass invasion and subsequent fire lead to widespread conversion from forest to grassland and increased frequency and severity of wildfire. While these 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.

Table 1. Live and dead fine fuel loads (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**	**Type**
								(P-value)	
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		-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		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

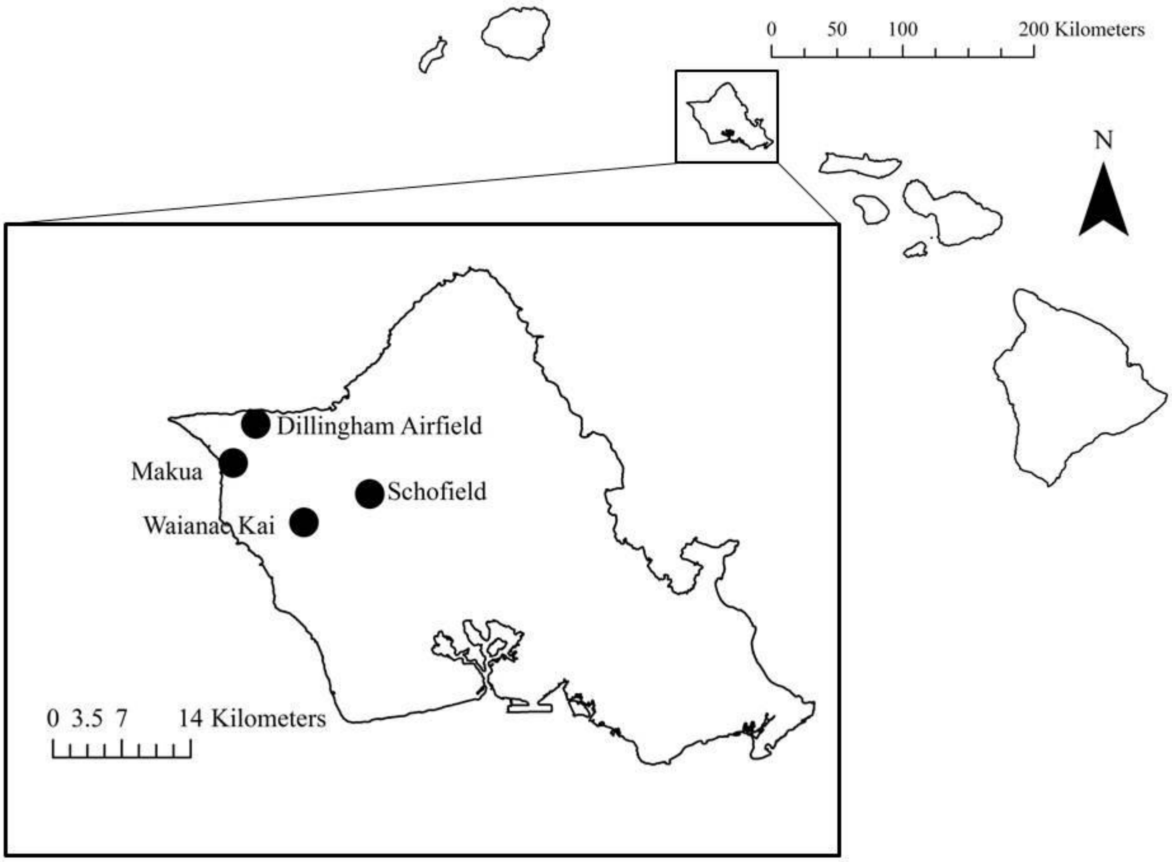

Figure 1. Location of sites for grassland and forest fuels sampling and historical analysis on the Waianae Coast and North Shores of Oahu, Hawaii. Forest and grassland field sampling occurred at Dillingham Airfield and Waianae Kai Forest Reserve. Historical land cover change analyses were conducted on imagery from Schofield Barracks and Makua Military Reservation.

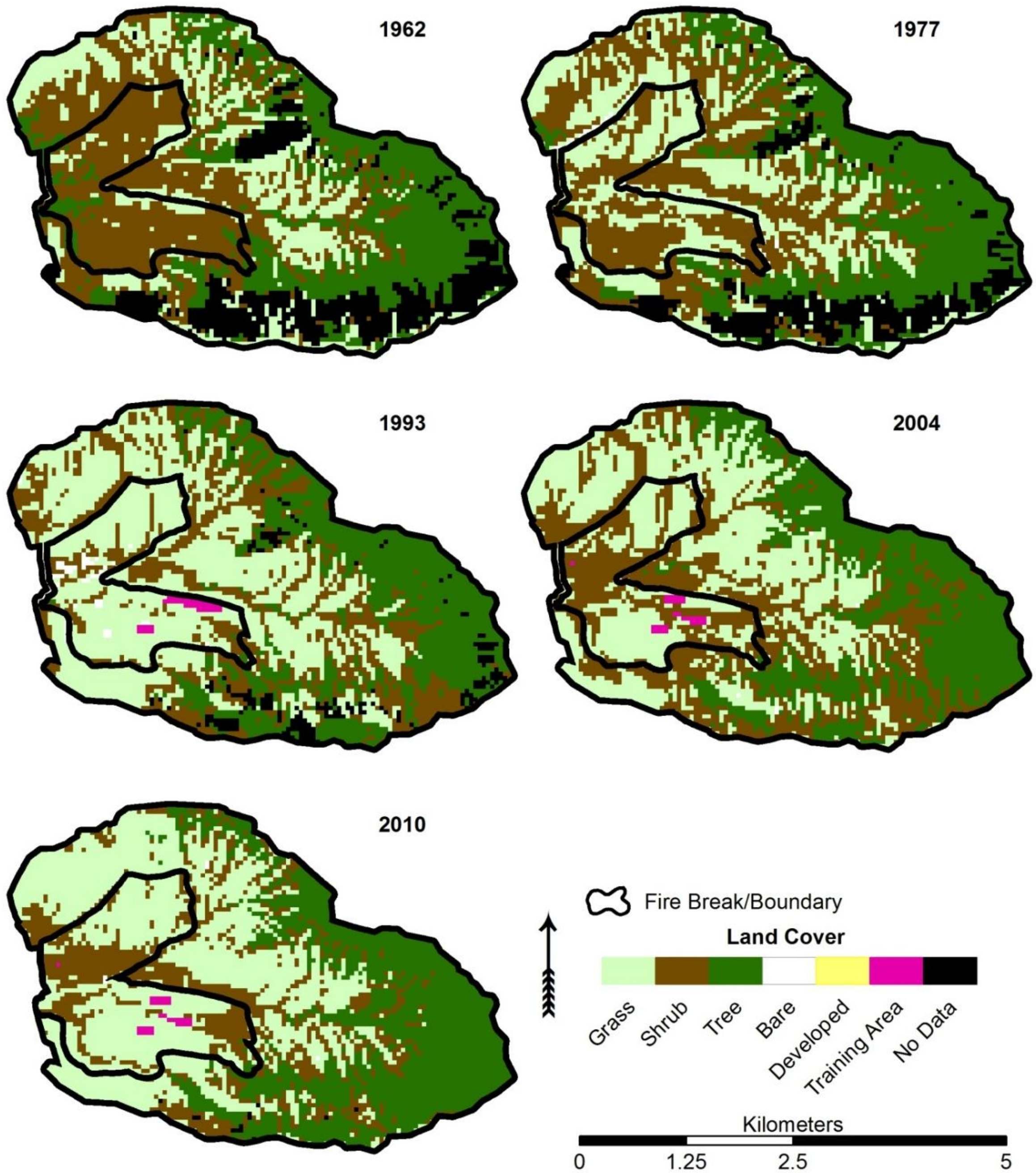

Figure 2. Land cover at Makua Military Reservation on leeward Oahu, Hawaii from 1962 through 2010. The area inside the firebreak is heavily utilized for military training activities, and fire is frequent. The area outside the firebreak has historically been forested, has many threatened and endangered species, and is impacted to a lesser extent by military activities and fire.

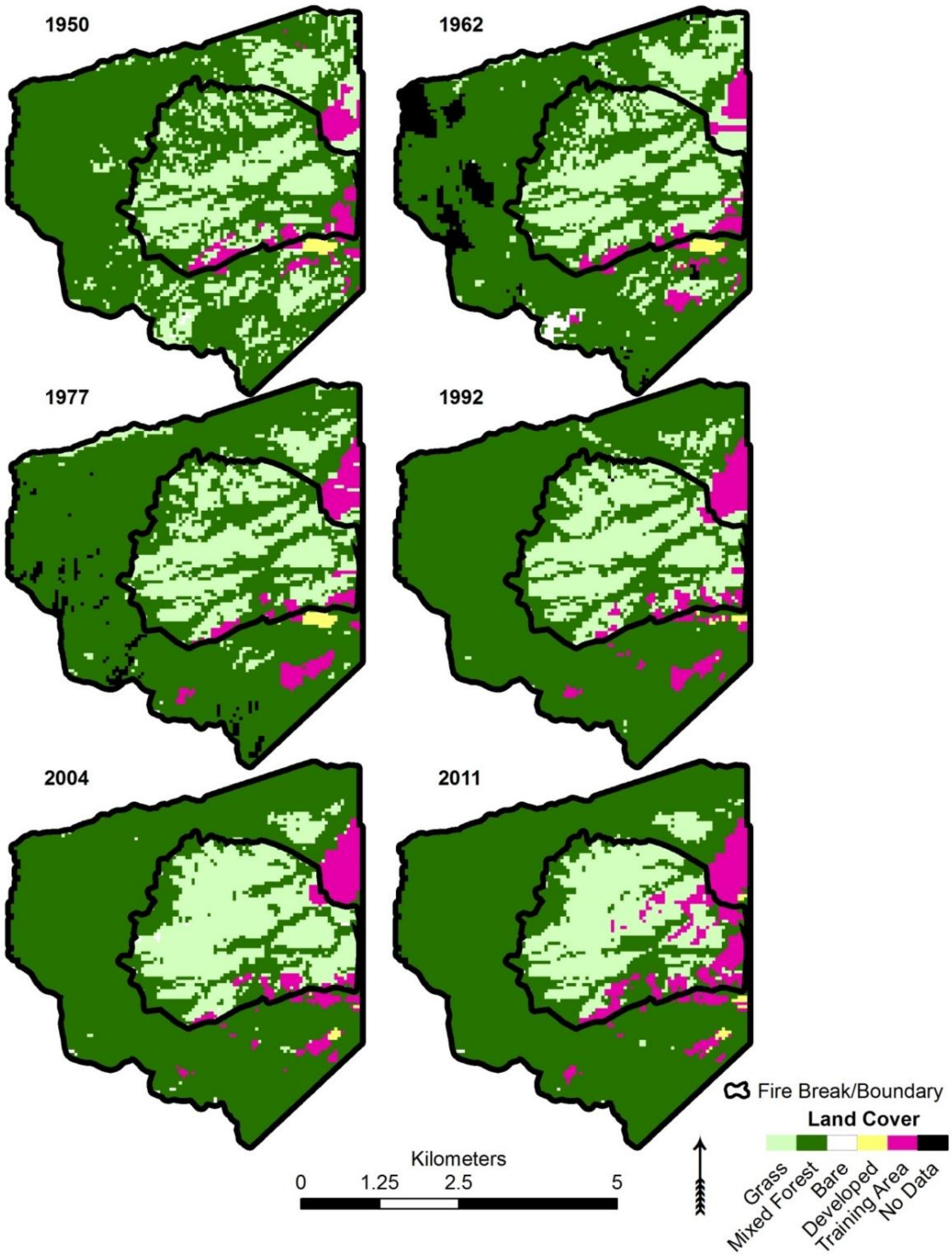

Figure 3. Land cover at Schofield Barracks on leeward Oahu, Hawaii from 1950 through 2011. The area inside the firebreak is heavily utilized for military training activities, and fire is frequent. The area outside the firebreak is maintained for woody species, and is less affected by military activity and fire.

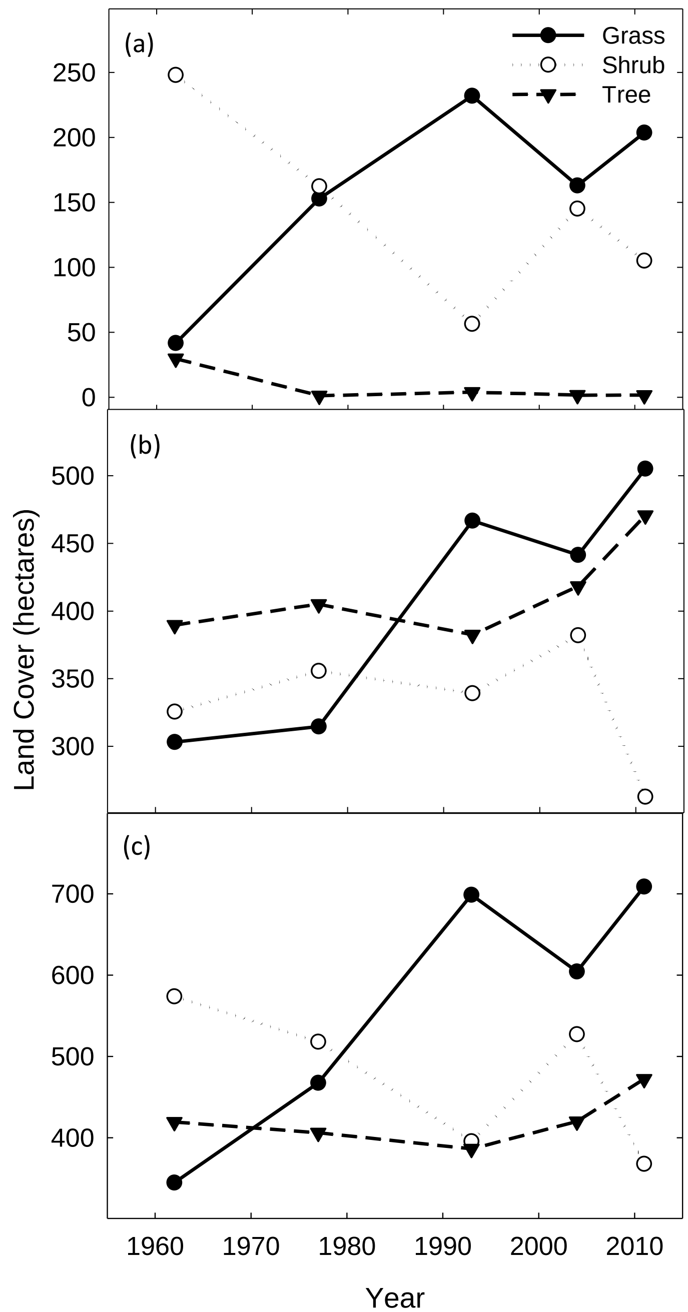

Figure 4. Change in grass, shrub, and tree land cover classes from 1962-2011 at Makua Military Reservation. Areas of interest (AIO) include: a) heavily utilized grassland area inside firebreak, b) nonnative forest area outside firebreak, and c) the entire Makua complex (both AOI's combined).

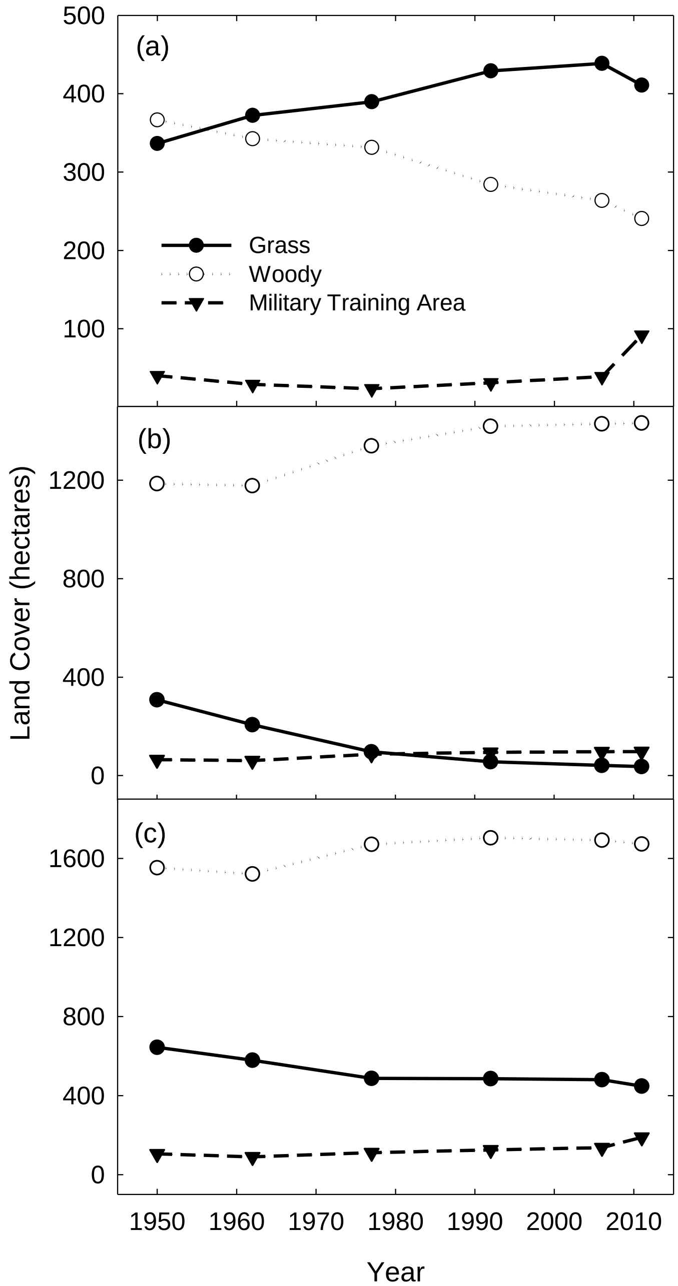

Figure 5. Change in grass, woody, and military training area land cover classes from 1950-2011 at Schofield Barracks. Areas of interest (AIO) include: a) heavily utilized grassland area inside firebreak, b) nonnative forest area outside firebreak, and c) the entire Schofield Barracks complex (both AOI's combined).

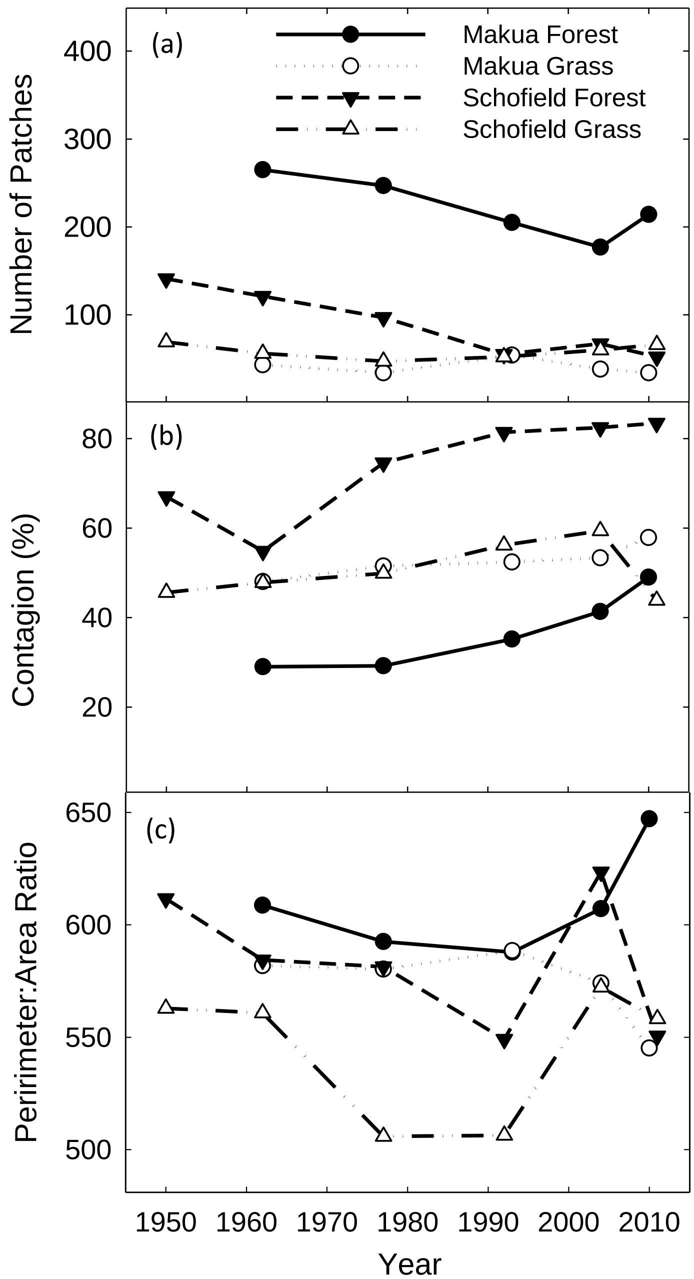

Figure 6. Landscape metrics: a) number of patches, b) contagion, and c) perimeter:area ratio for Forest and Grass areas of interest (AOI) at Schofield Barracks and Makua Military Reservation from 1950-2011

CHAPTER 3. SPATIAL AND TEMPORAL VARIABILITY OF GUINEA GRASS (*MEGATHYRSUS MAXIMUS*) FUEL LOADS AND MOISTURE ON OAHU, HAWAII

Abstract

Frequent wildfires in tropical landscapes dominated by nonnative invasive grasses threaten surrounding ecosystems and developed areas. To better manage fire, accurate estimates of the spatial and temporal variability in fuels are urgently needed. I quantified the spatial variability in live and dead fine fuel loads and moistures at four guinea grass (*Megathyrsus maximus*) dominated sites. To assess temporal variability, I sampled these four sites annually for three years, and also sampled fuel loads, moistures, and weather variables bi-weekly at three sites for one year. Live and dead fine fuel loads ranged spatially from 0.85 to 8.66 Mg ha^{-1} and 1.50 to 25.74 Mg ha^{-1}, respectively, and did not vary by site or year. Biweekly live and dead fuel moistures varied by 250% and 54%, respectively, and were closely correlated ($P<0.05$) with soil moisture, relative humidity, temperature, and precipitation. Overall, fine fuels and moistures exhibited tremendous variation, highlighting the importance of real-time, site-specific data for fire prevention and management. However, tight correlations with commonly quantified weather variables demonstrates the capacity to accurately predict fuel variables across large landscapes to better inform management and research on fire potential in guinea grass ecosystems in Hawaii, and throughout the tropics.

Introduction

The introduction and spread of invasive species is one of the leading causes of biodiversity loss in Hawaii (Loope, 1998; Loope, 2004; Loope et al., 2004; Hughes and Denslow, 2005). A cycle of positive feedbacks between invasive grasses and anthropogenic wildfire is now a reality in many Hawaiian landscapes formerly occupied by native woody communities (D'Antonio and Vitousek, 1992; Blackmore and Vitousek, 2000; D'Antonio et al., 2001). The synergistic interactions of fire and invasive species pose serious threats to the biological integrity and sustainability of remnant Hawaiian ecosystems (LaRosa et al., 2008). Coupled with frequent anthropogenic ignition sources, invasive grasses can dramatically increase fire frequency, often with severe consequences for native plant assemblages (Vitousek, 1992).

Guinea grass (*Megathyrsus maximus,* [Jacq.] B.K.Simon andS.W.L.Jacobs, previously *Panicum maximum* and *Urochloa maxima* [Jacq.]), originally from Africa, has been introduced to many tropical countries as livestock forage (D'Antonio and Vitousek, 1992; Portela et al., 2009). It was introduced to Hawaii for cattle forage and became naturalized in the islands by 1871 (Motooka et al., 2003). Guinea grass quickly became one of the most problematic nonnative invaders in Hawaiian landscapes because it is adapted to a wide range of ecosystems (*e.g*., dry to mesic) and can alter flammability by dramatically increasing fuel loads and fuel continuity. Year-round high fine fuel loads with a dense layer of dead grass in the litter layer maintain a significant fire risk throughout the year in guinea grass dominated ecosystems. In addition, this species recovers rapidly following fire by resprouting and seedling recruitment (Vitousek, 1992; Williams and Baruch, 2000). In Hawaii, as well as in many tropical areas, the conversion of land from forest to pasture or agriculture and subsequent abandonment has resulted in increased cover of invasive grasses across the landscape (Williams and Baruch, 2000). Because guinea grass recovers quickly following disturbances (*i.e.* fire, land use change, etc.) and is competitively superior to native species (Ammondt and Litton, 2012), many areas of Hawaii are now dominated by this nonnative invasive grass (Beavers, 2001) .

A small number of studies have examined fuel loads in guinea grass dominated ecosystems in Hawaii (Beavers et al., 1999; Beavers and Burgan, 2001; Wright et al., 2002). These prior studies, however, have been limited in spatial and temporal extent and their representativeness of the larger landscape is unknown. The reported variability in fuel loads in guinea grass stands in Hawaii is tremendous, ranging from 9.7 to 30.4 Mg ha^{-1}, but it is unknown what drives this variability. These overall values are similar to those reported for grass fuel loads in pastures in the larger tropics (Kauffman et al., 1998; Avalos et al., 2008; Portela et al., 2009). In cattle pastures of the Brazilian Amazon dominated by a similar grass species and in a similar climate, dead grass comprised 76 to 87% of the grass fuel load (Kauffman et al., 1998). These pastures were sampled less than two years after the previous fire, demonstrating that the rapid accumulation of dead fuels may be the primary driver of fire spread and behavior in these grasslands. Dead fuel moisture in guinea grass in Hawaii has previously been reported to show a strong diurnal pattern (>20% increase at night) and an over 50% increase in dead fuel moisture content after precipitation events (Weise et al., 2005). In similar tropical grasslands, variability in fuel moisture has been shown to be closely related to total fuel biomass and has been accurately predicted using climate variables (de Groot et al., 2005; Weise et al., 2005)

In Hawaii, little is known about fine fuel loads, one of the primary drivers of wildland fires. Research quantifying the spatial and temporal variability of fine fuels, ratio of live:dead fuels, fuel moisture content, and how these variables may relate to current and antecedent weather conditions and time since fire are largely lacking and urgently needed. To accurately predict and manage fire behavior in areas dominated by guinea grass fuels, it is imperative to first determine the spatial and temporal variability in guinea grass fuel loads, particularly for dry areas of the island (Giambelluca et al., 2011) where anthropogenic fire starts are common and risk of fire is greatest. In addition, it is imperative to determine what drives this spatial and temporal variability in fuel loads across the landscape to improve predictive capacity and better inform management decisions. Without improved fire prediction capability and rapid fire management response, wildland fires will continue to alter the composition and structure of these landscapes, contribute to the loss of native species diversity, and perpetuate the invasive grass/wildfire cycle in guinea grass dominated ecosystems.

The overall goal of this study was to conduct an assessment of the spatial and temporal variability in guinea grass fuels (live and dead fuel loads and moistures) on high fire risk areas on the Waianae Coast and North Shore of Oahu, Hawaii. Specific objectives included quantifying the: (*i*) spatial variability in live and dead fine fuel loads in guinea grass ecosystems in high fire risk areas; (*ii*) temporal variability at multiple scales (interannual, intraannual, and fine-scale [3x/week]) in fuel loads and fuel moistures in guinea grass ecosystems in high fire risk areas; and (*iii*) relationship between weather variables (precipitation, relative humidity, windspeed, and temperature) and fine fuel loads and moistures to explore predictive capacity to inform fire management of guinea grass ecosystems in Hawaii.

Methods

Spatial and interannual variability in guinea grass fuels

Research was initiated in the summer of 2008 to quantify the spatial and interannual variability of fuel loads in nonnative-dominated guinea grass ecosystems on Oahu's Waianae Coast and North Shore Areas (Figure 1). Sites were located at Schofield Barracks, Makua Military Reservation, Waianae Kai Forest Reserve, and Dillingham Airfield (Table 1) to encompass the widest range of spatial variability in environmental conditions occurring on the leeward, fire-prone area of Oahu. All sites have been heavily utilized by anthropogenic activity (*i.e.* military training, abandoned agricultural land) and are currently dominated by guinea grass with some invasive *Leucaena leucocephala* (Lam.) de Wit in the overstory. There is seasonal variability in precipitation patterns, with most precipitation falling in the winter months of November through April (Giambelluca et al., 2011). All study sites have deep, well drained soils which originated in alluvium and/or colluvium weathered from volcanic parent material (Table 1). Soils at Dillingham Airfield in the Lualualei series (fine, smectitic, isohyperthermic Typic Gypsitorrerts) formed in alluvium and colluvium from basalt and volcanic ash. At Makua, soils in some sample plots are also in the Lualualei series, and some have been classified broadly as Tropohumults-Dystrandepts. Soils at Waianae Kai are in the Ewa series (fine, kaolinitic, isohyperthermic Aridic Haplustolls) formed in alluvium weathered from basaltic rock. At Schofield Barracks, soils are in the Kunia series (fine, parasesquic, isohyperthermic Oxic Dystrustepts) which formed in alluvium weathered from basalt rock (Table 1).

Fuels were quantified by selecting and measuring at least three plots at each site. Six plots were sampled at Makua due to a wider range of expected fuel loads at this site. Plots were selected based on continuous grass and limited overstory tree cover using satellite imagery. Each plot was initially measured in the summer of 2008, and a subset of plots was remeasured in the summers of 2009 and 2010. One plot at Waianae Kai Forest Reserve and two plots at Schofield Barracks were abandoned after the 2008 sampling due to cattle and military activity, respectively, and the remaining two plots at Waianae Kai were abandoned due to cattle activity after the 2009 sampling.

Fuel parameters measured during yearly plot visits were: (*i*) total fine fuel loads (standing live and dead, and litter), (*ii*) fuel composition (live and dead grass and herbs), and (*iii*) fuel moisture content for both live and dead grass fuels. At each 50 x 50 m sampling 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 regularly-spaced fixed locations along each transect (n=18/plot). Subsequent years' samples were offset 3 m from previously clipped subplots. Samples were separated into the following categories: live grass, live dicots, standing dead grass, standing dead dicots, and surface litter. Samples were collected, placed into plastic bags to retain moisture, weighed within 6 hours of collection, dried in a forced air oven at 70^{o}C to a constant mass, and re-weighed to determine dry mass and moisture content relative to oven dried weight. Some live and dead woody fuels existed in my study sites, but I was primarily interested in characterizing fine fuels associated with guinea grass, so did not include woody fuels in my analyses. Overall, live trees were infrequent in most plots, comprising only 5.8% of the total fuel load on average (range of 0-22%). Dead woody fuels, in turn, constituted only 0.5% of the total fuel load on average (range of 0-5%).

Intraannual temporal variability in guinea grass fuels

Intraannual variability of live and dead fuel loads and moisture content was measured approximately biweekly (27-33 sample dates per site) for one year (October 8, 2009 through September 24, 2010) in three plots on leeward Oahu – Dillingham Ranch (immediately adjacent to the Dillingham Airfield sites), Schofield Barracks, and Yokohama State Park (proxy for adjacent Makua, where access is limited due to unexploded ordinance; Figure 1; Table 1). All sites were dominated by guinea grass, with scattered *L. leucocephala* in the overstory. Soils at Schofield are in the Kunia series and soils at Yokohama are in the Lualualei series (see soils descriptions above). At Dillingham Ranch, soils are in the Kawaihapai series (fine-loamy, mixed, superactive, isohyperthermic Cumulic Haplustolls), which are well drained soils that formed in alluvium derived from basic igneous rock (Table 1).

At each sampling location, one 50m transect was established per sample date, along which all vegetation and litter in 25x50 cm subplots at 6 locations (0, 10, 20, 30, 40, and 50m marks) was clipped and collected. Each subsequent transect was offset one meter from and parallel to the previous sampling transect, with all transects running parallel to the slope. Live and dead (standing dead and litter combined) fine fuels were processed for moisture content and total dry weight, as described above. Additionally, soil volumetric water content in the top 12 cm of mineral soil was quantified in every subplot at each sampling date with a CS620 HydroSense Water Content Sensor (Campbell Scientific, Logan, Utah). Six measurements were taken adjacent to each subplot, and averaged across subplots for each sampling date.

Fine-scale temporal variability in guinea grass fuels

To gain a better understanding of changes in fuel moistures following precipitation events at a finer temporal resolution, I measured live and dead fuel moistures three times per week for 4 weeks at the Dillingham Ranch site. The first sampling event corresponded to the first week of Fall rains (November 1, 2010). At each sampling date, six randomly located samples of live grass and standing dead grass were collected, one each from six randomly located sampling locations. Vegetation samples were processed to determine moisture content as described above.

Analysis of spatial and interannual temporal variability of guinea grass fuels

Due to significant imbalance and heteroskedasticity in the data, I used a repeated measures mixed model analysis to determine whether differences exist in fine fuels which could be attributed to site (spatial) or year sampled (temporal) variability. Response variables examined in separate analyses were live fine fuels (live grass + live herbs), dead fine fuels (standing dead grass + litter + dead herbs), and total fine fuels (all live and dead fine fuel components). Plots were treated as subjects, to account for the repeated measurements taken over time. Site was treated as a fixed factor, year was treated as a random factor, and the interaction between site and year was tested to determine whether there was a differential pattern over time at separate sampling sites. Restricted maximum likelihood estimates (REML) of parameter values were derived using IBM SPSS v.20 (IBM SPSS, Inc., Chicago, IL) and SAS 9.2 for Windows (SAS Institute Inc., Cary, NC, USA). REML is preferred to maximum likelihood (ML) as it gives unbiased estimates of covariance parameters by taking into account the loss of degrees of freedom from estimating the fixed effects in the model (West et al., 2007). At least four covariance structures were considered for each response variable, and the best fitting structure was chosen based on available information criterion (-2 log likelihood, Akaike's Information Criterion, Schwarz's Bayesian Criterion) (West et al., 2007). A heterogeneous Toeplitz structure was selected for all response variables. Significance of random effects was determined by REML-based likelihood ratio tests between full and reduced models (West et al., 2007; McCulloch et al., 2008). Significance of fixed site effect was determined by least squares F-tests, with significance determined at α=0.05. Post-hoc multiple comparisons using the least square difference method were performed to elucidate differences between individual sites.

Analysis of intraannual temporal variability of guinea grass fuels

A repeated measures mixed model analysis was used to determine whether there was a difference in fine fuel load or fuel moisture which could be attributed to site or time sampled. Additionally, I was interested in potential relationships between fuel load and fuel moisture, and onsite weather variables (antecedent precipitation, maximum windspeed, relative humidity, and air temperature). Response variables examined in separate analyses were live fine fuels (live grass and live herbs), dead fine fuels (standing dead grass, litter, and dead herbs), total fine fuels (all live and dead fine fuel components), live fuel moisture content, and dead fuel moisture content. Site and sample week were both treated as fixed factors, as I was interested in all the levels of each factor. Weather data were downloaded from onsite Remote Automated Weather

Stations (RAWS) at each sampling site, and variables were chosen as covariates based on bivariate correlations between weather and response variables. An iterative backwards model selection process was used to determine which explanatory variables contributed to the best model fit, starting with a full model with all covariates and two-way interactions but without the site and time factors. The model was iteratively reduced by removing terms which were not significant by least-squares F-tests at $\alpha=0.05$. After the best covariate-only model was determined, site and time factors were added to see if they explained any additional variability in the data. Weather covariates considered in each model were 7 day antecedent precipitation (Precip), 7 day average maximum air temperature (Temp), and 7 day average minimum relative humidity (RH). Additionally, soil moisture content (SM) was included as a potential explanatory covariate. While fuel parameters, particularly fuel moisture can change on very short time scales (*i.e.* hourly) (Viney, 1991), for fire management (*i.e.* planning prescribed fires, estimating needed suppression resources, etc.) it is also useful to understand how longer scale (*ie* daily, weekly) climate patterns affect fuel moisture. After examining relationships between weather variables at multiple intervals (daily, 3, 5, 7, 10, and 14 day averages), 7 day average provided the most effective relationship with fuel moisture. REML estimates of parameter values were derived using IBM SPSS v.20 (IBM SPSS, Inc., Chicago, IL). At least four covariance structures were considered for each response variable, and an autoregressive structure was chosen based on available information criterion for all response variables. Significance of fixed effects was determined by least squares F-tests at $\alpha=0.05$, and post-hoc multiple comparisons using the least square difference method were performed to elucidate differences between individual sites.

Analysis of fine scale temporal variability of guinea grass fuels

The change in live and dead fine fuel moisture at the finer temporal resolution (3 times per week for 4 weeks) was analyzed using backwards stepwise linear regression, with weather covariates derived from onsite RAWS as described above (Precip, Temp, RH). Additionally, 7 day average maximum sustained windspeed (Wind) was used as a covariate. Because I wanted to see how antecedent weather altered fuel moisture between sampling dates, I used the change (Δ) in live and dead fuel moistures from one sampling date to the next as the response variables. All covariates and two way interactions between covariates were considered for inclusion in linear regression models, and were iteratively removed based on non-significant F-tests, with $\alpha = 0.15$ used as the criteria to enter or remove terms from possible models.

Results

Spatial and interannual temporal variability in guinea grass fuels

Total fine fuel loads ranged widely across sites and years, from 3.26 to 34.29 Mg ha^{-1}. Total fine fuels did not vary significantly by site (P=0.17). Live and dead fine fuel loads ranged from 0.85 to 8.66 Mg ha^{-1} and 1.50 to 25.74 Mg ha^{-1}, respectively. Neither live (P=0.29) nor dead (P=0.11) fine fuels varied by site. At all four sites, there was more dead fine fuel (standing dead leaves and sheaths and litter) than live fine fuel, with the live:dead ratio ranging from 0.21 in plots at Makua to 0.65 at Schofield Barracks.

The among-years variance component for total fine fuel loads was estimated to be zero (P=1.00), indicating that there were no consistent year effects across all sites. There was, however, strong evidence that sites varied differently over time (site*year interaction; P<0.01; Figure 2). Makua and Schofield showed a trend of increasing fine fuel loads over time, while Waianae Kai had fairly constant fuel loads over time and Dillingham site had highest fine fuel loads in 2009. Similarly, there was no consistent year effect in either live (P=1.00) or dead (P=1.00) fine fuel loads, but the change in both live and fine fuels over time differed across sites (site*year interaction, P<0.01 for both dead and live; Figure 2)

Intraannual temporal variability in guinea grass fuels

There was considerable temporal variability in total fine fuel loads on a bi-weekly scale at all three sampled sites (intraannual temporal sites, Figure 1). While total fuel loads varied considerably from one sample date to the next, there was a general trend of higher fuel loads in the late spring and early summer than in the fall and winter (Figure 3). Weather covariates and soil moisture were poor predictors of total fine fuels (Table 2). The best model for total fine fuels contained only the site factor (P<0.01), with both

Dillingham Ranch (*P*<0.01) and Schofield Barracks (*P*<0.01) having significantly more total fine fuels than Yokohama (Figure 3, Table 2).

Soil moisture (*P*=0.01), Temp (*P*<0.01), RH (*P*<0.01), and the Temp*RH interaction (*P*<0.01), were all significant predictors of the variability in live fine fuel loads over the sampled year (Table 2). In a model including these weather covariates, increases in temperature (model estimate = 2.94) and relative humidity (estimate =1.91) increased live fine fuel loads, while increases in soil moisture (estimate = -0.11) and in the Temp*RH interaction (estimate = -0.06) resulted in small decreases in live fine fuels. Live fine fuel loads varied by site (*P*<0.01), with lower fuels at Yokohama (1.28-6.30 Mg ha^{-1}) than either Dillingham Ranch (2.12-14.80 Mg ha^{-1}; *P*<0.01) or Schofield Barracks (3.20-15.16 Mg ha^{-1}; *P*<0.01).

Weather and soil moisture covariates were not strong predictors of the variability in dead fine fuels (Table 2). Differences based on study site were marginally significant (*P*=0.06, Table 2), with more dead fine fuel at Dillingham Ranch (8.19-28.61 Mg ha^{-1}; *P*=0.03) and Schofield Barracks (8.19-29.39 Mg ha^{-1}; *P*=0.04) than at Yokohama (9.01-23.09).

Moisture content of fine fuels was quite variable over time, with large changes seen between sampling weeks (Figure 5). Weather covariates and soil moisture were good predictors of the measured changes in live and dead fuel moistures over the year sampled. The best model for live fuel moisture included soil moisture (estimate = 2.90; *P*<0.01), Temp (estimate = -39.06; *P*<0.01), RH (estimate = -15.63; *P*=0.06), and the Temp*RH interaction (estimate = 0.63; *P*=0.03, Table 2), and there was no evidence for additional variability in the data being explained by site differences (*P*=0.23). Live fuel moisture was generally higher in the Winter and Spring than in the Summer and Fall, but rapid changes were often seen between sampling dates with changes in weather events (e.g., precipitation).

Dead fine fuel moisture was similarly lowest in the Summer and Fall across all three sites, with higher moistures and greater variability measured in the Winter and Spring. The model that best explained the variability seen in dead fuel moisture included soil moisture (estimate = 0.39; *P*<0.01), Temp (estimate = 4.24; *P*<0.01), RH (estimate =

2.98; *P*<0.01), Precip (estimate 1.56; *P*=0.02), Temp*RH (estimate = -0.09; *P*<0.01), and Temp*Precip (estimate = -0.05; *P*=0.02, Table 2), but not sample site (*P*=0.10).

Fine-scale temporal variability in guinea grass fuels

At a finer temporal scale (3 sampling dates per week for four weeks), fuel moisture could not be accurately predicted using selected weather covariates. While there appeared to be a trend of increasing fuel moisture following rainfall events (Figure 5), predictive relationships between weather variables and fuel moisture were not evident with the data collected. Live fuel moisture was lowest (115%) on the first sampling date. After a week with multiple rainfall events, live fuel moisture increased to >300% and remained high (between 195-304%) for the duration of the sampling period. Relationships between antecedent weather and change in live fuel moisture were quite weak. There was a suggestive correlation between relative humidity and live fuel moisture (r^2 = 0.63, *P*=0.05). Models generated using stepwise linear regression explained little of the variability in the data, and none were statistically significant. The best model ($\Delta LFM = -382 - 4.35Wind + 9.20RH$; *P* = 0.11) included only 7 day average maximum windspeed (kph) and 7 day average minimum relative humidity (%) as predictor variables, with no significant interactions, but this model was not statistically significant; in addition, although this model explained nearly half the variation in the response variable (r^2 = 47.3%), its predicted r^2 (IBM SPSS, Inc., Chicago, IL) was much lower (r^2_{pred} = 14.3%), suggesting that even this simple model was overfitting the data.

Dead fuel moisture was much less variable than live fuel moisture, ranging from 14.5% to 27.0% throughout the sampling period. Relative humidity (7 day average minimum) was again the only weather variable significantly correlated with change in dead fuel moisture between sampling dates (r^2 = 0.70, *P*=0.04). Models generated using stepwise linear regression explained little of the variability in the data, and had no predictive power. The best model ($\Delta DFM = -141 + 1.26Temp + 2.07RH - 0.279Precip$: r^2 = 74.5%; r^2_{pred} = 0.0%; *P* = 0.11) included only 7 day average maximum temperature (C), 7 day average minimum relative humidity (%), and 7 day antecedent precipitation (mm) as predictor variables, with no significant interactions.

Discussion

The distribution and arrangement of fuel loads profoundly affect fire behavior across a landscape (Rothermel, 1972; Pyne et al., 1996). Invasive grasses in the tropics alter fuel loads, providing a continuous, highly flammable fuel source which perpetuates a cycle of fire and further grass invasion (D'Antonio and Vitousek, 1992; Brooks et al., 2004). A better understanding of the spatial and temporal variability in fuel loads and moistures associated with invasive grasses is, therefore, integral to fire prevention and management in these ecosystems.

Previous work on guinea grass fuel loads has shown that there is great variability in this fuel type, but the spatial and temporal scope of these studies has been limited (Beavers et al., 1999; Beavers, 2001; Wright et al., 2002; Weise et al., 2005). In Brazil, pronounced temporal variability in guinea grass fine fuel loads has been documented, with live fine fuel loads ranging from <1 to 12.5 Mg ha^{-1}, and dead fine fuel loads from 2.5 to 19.0 Mg ha^{-1}(Portela et al., 2009). Similar variability was reported over a 7 year study period in Puerto Rico, where total fine fuel loads ranged from 3.6 to 14.3 Mg ha^{-1} (Francis and Parrotta, 2006).

My results show even greater variability in guinea grass fuel loads, but generally support previously published estimates. Importantly, total fuel loads in mature guinea grass stands can vary remarkably, both spatially and temporally, over a relatively small island landscape. My data, like previous work, do not provide clear evidence for seasonal patterns in fuel loads (Table 2). Rather, fluctuations over shorter time periods driven by weather characterize this landscape. The differing temporal patterns observed between sites in this study may be due to small scale weather patterns (*i.e*. precipitation events, solar radiation, wind speed and direction), as well as land use and management histories (*e.g*., military training vs. state park). More dead fuel loads than live were consistently observed in this study across all sites and sampling periods, translating to landscapes with high ignition potential year-round. In tropical grassland fuel types, fire will no longer spread when dead fuel moisture is above a threshold of ~30-40% moisture content (Beavers, 2001; Scott and Burgan, 2005). Dead fuel moisture in all sampled sites was well below this threshold at many sampling periods (Figure 4), indicating that these sites have adequate fuel accumulation and sufficiently low fuel moisture content to promote rapid fire spread most of the time.

Live fuel moisture, which is affected by both biological processes and current and antecedent weather, also affects potential fire behavior on the landscape. Water is a heat sink, and must be removed from at least the surface layer of the fuel before ignition is possible. When live fuel moisture is high, ignition is unlikely but as live fuel moisture decreases, potential for ignition increases (Pyne et al., 1996). Rapid increases in live fine fuel moisture were observed in this study following precipitation events when relative humidity was high, temperatures were low, and soils were moist. Additionally, an interactive effect of temperature and relative humidity was evident, such that fuel moisture stayed higher when weather was cool and moist.

Prediction of fuel parameters using weather covariates was most effective in intraannual temporal models. Live and dead fuel moisture had strong relationships with weather covariates (Temp, RH, Soil Moisture, Precip; Table 2). Fuel moisture is one of the most difficult parameters to predict, but one of the most important parameters determining fire ignition and spread. Development of robust, site-specific predictive capacity for fuel moisture, such as that provided here, will greatly advance fire modeling capacity in tropical landscapes.

While my intraannual models showed good prediction capacity over the year sampled, the most valuable model would be one that could be used on shorter time scales, giving managers almost real-time information about fuel moisture conditions. In my fine scale variability sampling, it appeared that periods of increased fuel moisture followed precipitation events (Figure 5), as would be expected, but models describing this relationship on short time scales (*i.e.* daily to weekly) were not effective for prediction, perhaps due to the small sample size. The change in live and dead fuel moisture may be a product of many interacting factors, including current and antecedent weather (temperature, precipitation, windspeed and direction, insolation, relative humidity, etc.) as well as physical and biological processes (soil moisture, soil water holding capacity, evapotranspiration, plant water uptake, species specific curing rates, etc.) (Viney, 1991; Viney and Catchpole, 1991; Cheney et al., 1993; Nelson Jr, 2000; Weise et al., 2005). These complex interactions may make prediction of live and dead fuel moisture difficult on short time scales, but at longer temporal scales (intrannual), these relationships improved.

This research provides an important first step in the management and prevention of fire in guinea grass dominated ecosystems in Hawaii by making available a data set describing the variability of fuel loads over both space and time. The conversion of native, lowland dry ecosystems to invasive dominated, fire-prone grass ecosystems has increased the demand on fuels and fire management agencies. Important future work in guinea grass ecosystems in Hawaii, other island ecosystems, and throughout the tropics will be the incorporation of the data presented here into fire prediction modeling tools, such as fire behavior and spatial models. Additional on fuel height, arrangement, and continuity will be important for scaling these models across larger spatial scales. With this knowledge, managers will be better able to assess potential fire risk and consider management strategies in guinea grass dominated ecosystems in Hawaii and throughout the tropics.

Table 1. Descriptions of sites sampled for spatial variability in fuel loads and temporal variability in fuel loads and fuel moisture.

Site	**Elevation (m.a.s.l)**	**MAP (mm)[a]**	**MAT (°C)[b]**	**Soil Classification[c]**
Dillingham Airfield	4	900	24	Lualualei Series: Typic Gypsitorrerts
Dillingham Ranch	5	851	24	Kawaihapai Series: Cumulic Haplustolls
Makua	108	864	23	Tropohumults-Dystrandepts and Lualualei Series: Typic Gypsitorrerts
Schofield Barracks	297	1000	22	Kunia Series: Oxic Dystrustepts
Waianae Kai	193	1134	23	Ewa Series: Aridic Haplustolls
Yokohama	7	857	24	Lualualei Series: Typic Gypsitorrerts

[a]Mean Annual Precipitation (Giambelluca et al., 2011)

[b]Mean Annual Temperature (T. Giambelluca, *unpub. data*)

[c](Soil Survey Staff, 2006)

Table 2. Statistical results of separate repeated measures mixed model analyses for intraannual temporal variability models.

Model[a]	Parameter	Estimate	SE	df	t-statistic	p-value
Total Fine Fuel Biomass (Mg ha^{-1})						
	Intercept	18.65	1.85	16.17	10.09	0.000
	Site					
	site = Dillingham	9.68	2.60	15.83	3.72	0.002
	site = Schofield	7.89	2.66	16.92	2.97	0.009
	site = Yokohama	0.00[b]	0.00[b]	.	.	.
Live Fine Fuel Biomass (Mg ha^{-1})						
	Intercept	-84.02	28.75	38.62	-2.92	0.010
	Site					
	site = Dillingham	5.15	1.04	40.85	4.96	0.000
	site = Schofield	3.07	0.86	26.93	3.56	0.001
	site = Yokohama	0.00[b]	0.00[b]	.	.	.
	Temp	2.94	0.96	36.82	3.06	0.004
	RH	1.91	0.54	37.65	3.52	0.001
	Soil Moisture	-0.11	0.04	74.89	-2.62	0.011
	Temp*RH	-0.06	0.02	35.70	-3.45	0.001
Dead Fine Fuel Biomass (Mg ha^{-1})						
	Intercept	14.65	1.32	14.64	11.10	0.000
	Site					
	site = Dillingham	4.37	1.86	14.37	2.35	0.034
	site = Schofield	4.33	1.89	15.31	2.29	0.037
	site = Yokohama	0.00[b]	0.00[b]	.	.	.
Live Fine Fuel Moisture (%)						
	Intercept	1119.87	415.38	46.60	2.70	0.010
	Temp	-39.06	14.03	43.35	-2.78	0.008
	RH	-15.63	8.00	46.39	-1.95	0.057
	Soil Moisture	2.90	0.44	76.05	6.59	0.000
	Temp*RH	0.63	0.28	43.15	2.29	0.027
Dead Fine Fuel Moisture (%)						
	Intercept	-136.54	39.61	44.88	-3.45	0.001
	Temp	4.24	1.30	44.00	3.27	0.002
	RH	2.98	0.78	46.85	3.81	0.000
	Soil Moisture	0.39	0.06	47.63	7.03	0.000
	Precip	1.56	0.65	74.96	2.40	0.019
	Temp*RH	-0.09	0.03	45.71	-3.32	0.002
	Temp*Precip	-0.05	0.02	73.70	-2.33	0.023

[a] Estimation method: REML software: SPSS:MIXED
[b] Yokohama set as reference site

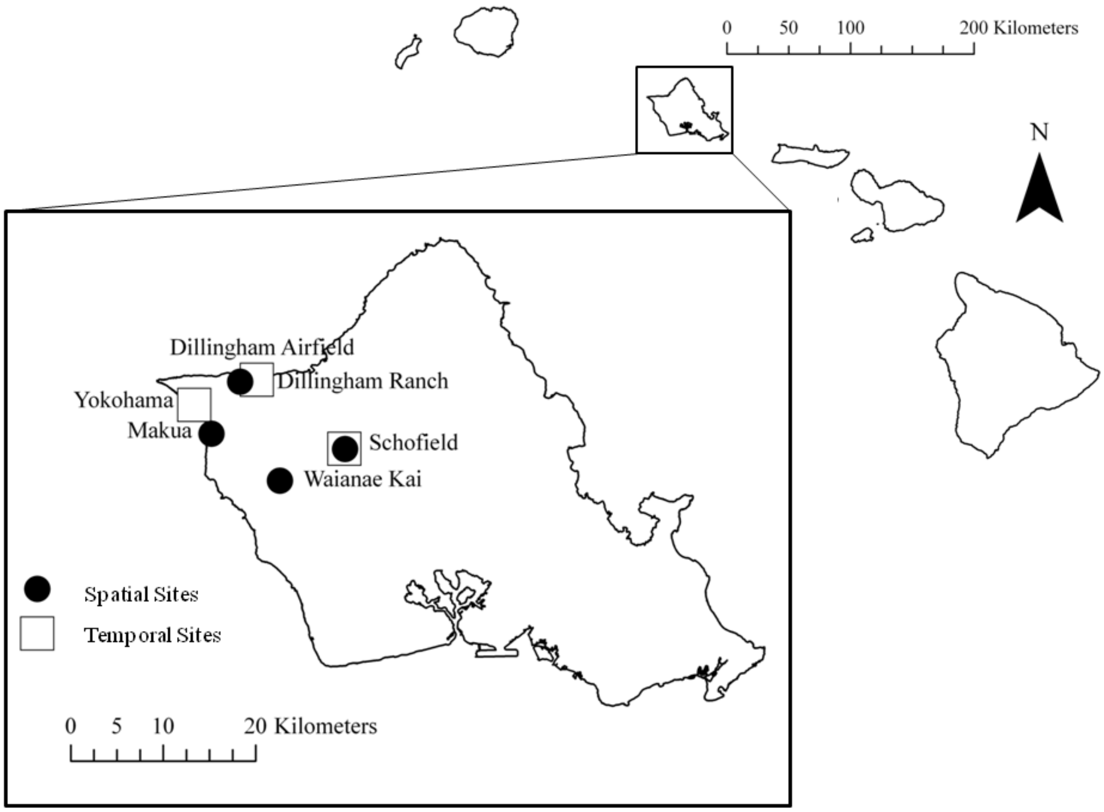

Figure 1. Location of sample sites for spatial and temporal variability sampling in fuel loads across the Waianae Coast and North Shores of Oahu, Hawaii. Black circles indicate sites that were sampled during the summers of 2008, 2009, and 2010 (Spatial and Interannual Temporal Sites). White squares indicate sites that were sampled biweekly for one year (Intraannual Temporal Sites). Sites with both a black circle and a white square were used for both spatial and temporal sampling.

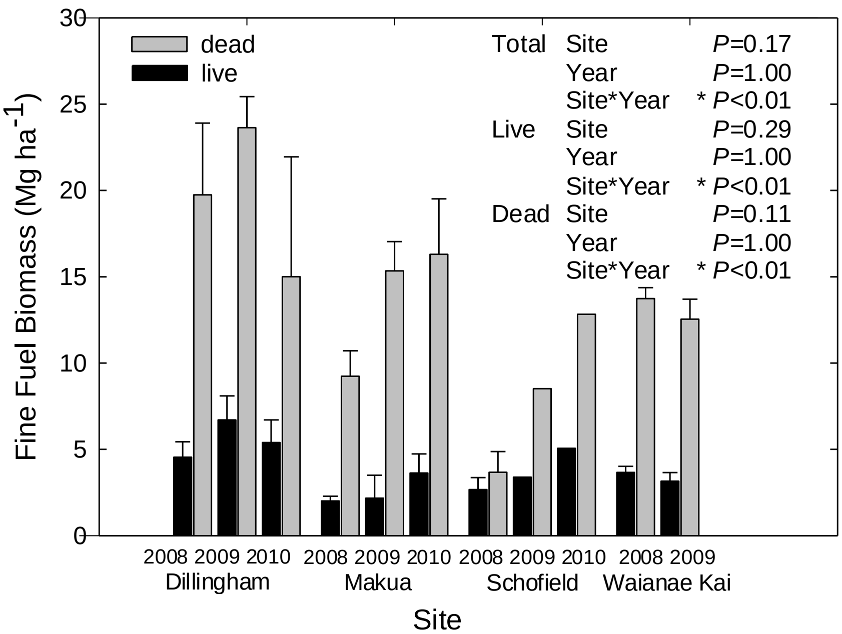

Figure 2. Spatial variability in aboveground fine fuels in four guinea grass dominated sites along the Waianae Coast and North Shore areas of Oahu, Hawaii from 2008-2010. Bars are means for each site (Mg ha^{-1}), and error bars represent one S.E. Gray bars denote dead fine fuel loads, and black bars live fine fuel loads.

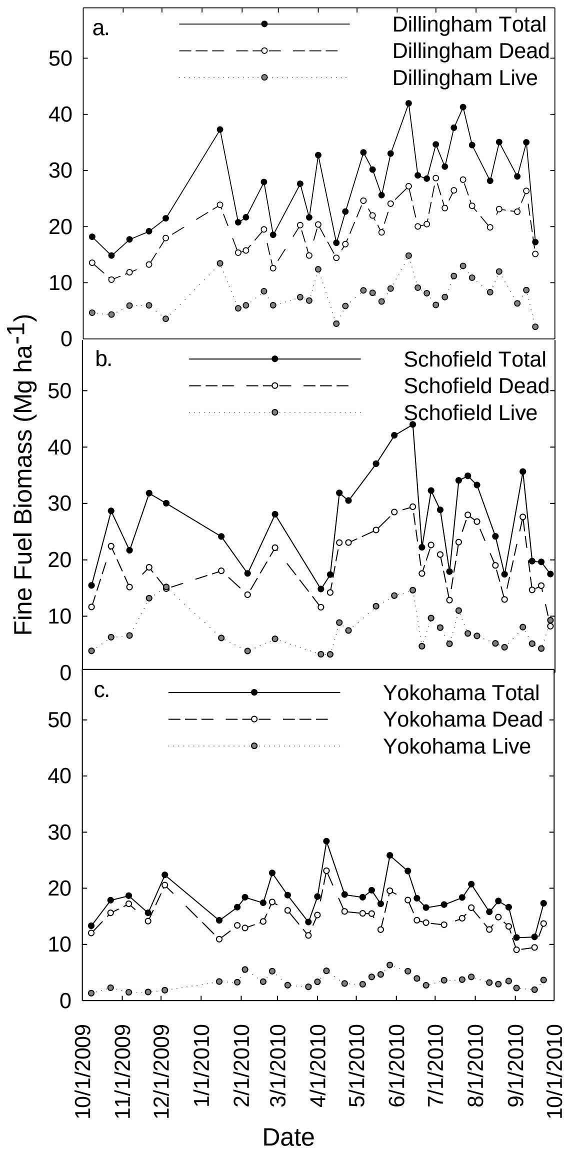

Figure 3. Intraannual temporal variability in aboveground fine fuels at three guinea grass dominated sites on Oahu, Hawaii from October 2009-September 2010.

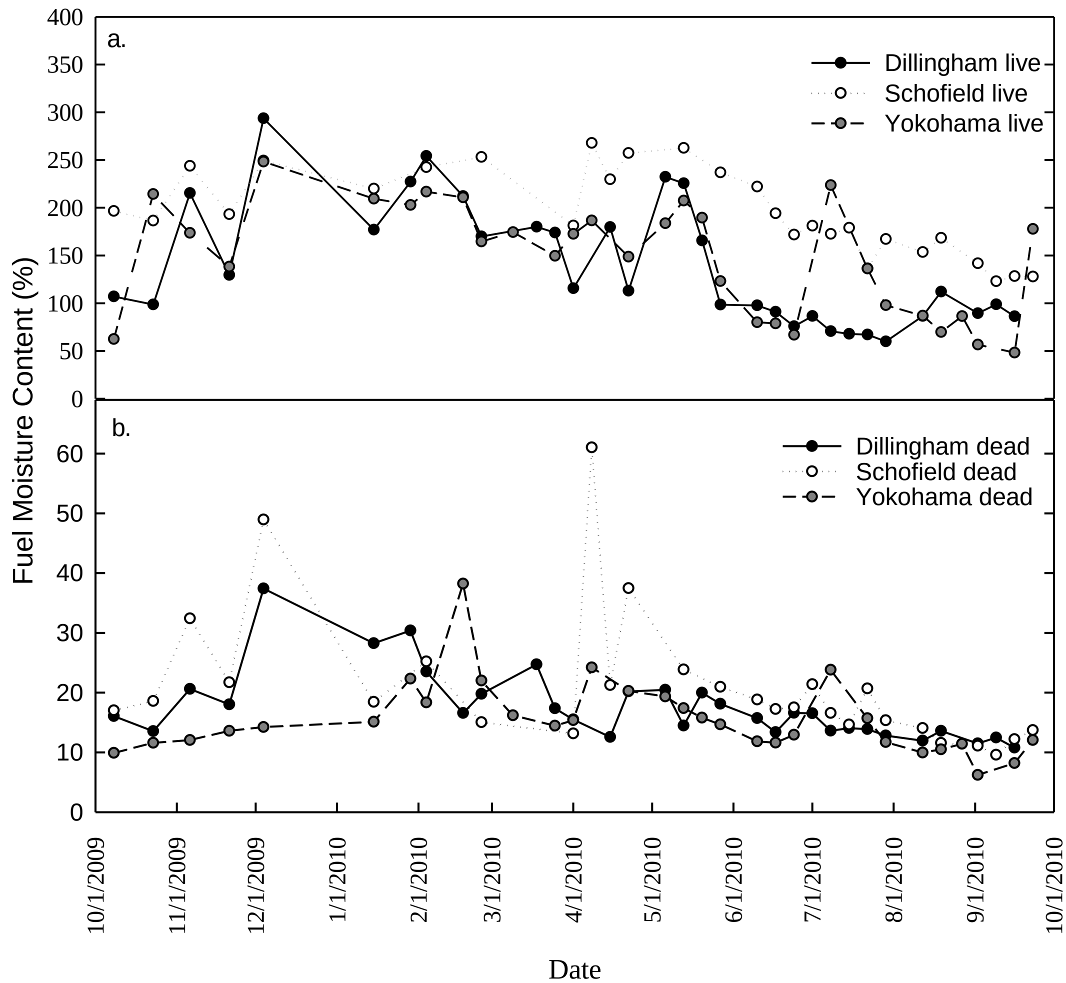

Figure 4. Intraannual temporal variability in (a) live and (b) dead fuel moistures at three guinea grass dominated sites from October 2009-September 2010 (note: different scales on y-axis).

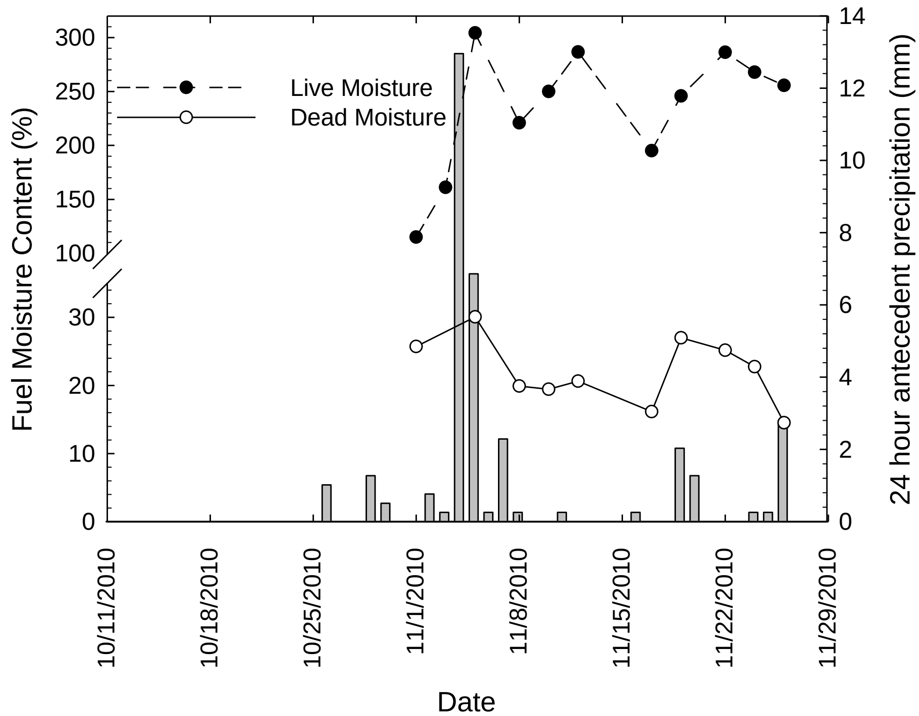

Figure 5. Fine scale temporal variability in fine fuel moisture at Dillingham Ranch on Oahu, Hawaii over four weeks. Vertical bars denote rainfall events (mm; right y-axis) for the three weeks prior to, and during sampling. Dates without bars had no precipitation. Dashed line with closed circles denotes live fuel moisture, and solid line with open circles denotes dead fuel moisture.

CHAPTER 4. A CUSTOM FUEL MODEL FOR NONNATIVE GUINEA GRASS (*MEGATHYRSUS MAXIMUS*) ECOSYSTEMS IN HAWAII

Abstract

The interactive influences of repeated fire and grass invasion in tropical dry forest ecosystems often threaten adjacent ecosystems and developed areas. To better manage fire in these ecosystems, improved models of fire potential and behavior are urgently needed. Predicting fire behavior is commonly accomplished with fire models, but their real-world utility requires accurate, field-based fuel and microclimate inputs to parameterize the models. The objective of this study was to create a custom guinea grass (*Megathyrsus maximus*) fuel model based upon field-based fuel measurements and *in situ* climate data, for use in the BehavePlus fire modeling software, that accurately predicts the spread of fire through guinea grass dominated ecosystems in Hawaii, and ideally throughout the tropics. I hypothesized that this custom fuel model (GG2012) would perform better than either national tall grass fuel models (Grass 3, GR8, GR9) or previous custom models for guinea grass in Hawaii (Beavers Grass 2) because *in situ* species-specific fuels data were used in its parameterization. Custom and standard models were tested using data from five prescribed fires in guinea grass dominated ecosystems in Hawaii. Custom fuel model parameters were markedly different from standard models, with 69-922% more 1-hr fuels and a much lower live herbaceous fuel load. The resulting high dead:live fuel ratio in the custom model that was based on empirical field data resulted in moderate predicted rates of spread (8.1-16.7 m min^{-1}) under the lowest fuel moisture scenarios, and high flame lengths (2.4-5.9 m) throughout all but the highest fuel moisture scenarios. Of all models tested, the custom model (GG2012) output best matched observed rates of spread. These results suggest that a field based fuel model, while time intensive to develop, can improve the accuracy of fire behavior modeling, thereby increasing capacity for land managers to manage fire in *M. maximus* dominated ecosystems.

Introduction

Hawaii has a significant problem with wildland fires, particularly in landscapes where native woody communities have been invaded and replaced by nonnative grasses (Vitousek, 1992; D'Antonio et al., 2000). Wildfires in Hawaiian ecosystems dominated by invasive grasses such as guinea grass (*Megathyrsus maximus*, [Jacq.] previously *Panicum maximum* and *Urochloa maxima* [Jacq.]), are almost exclusively the result of anthropogenic ignitions (Beavers, 2001). These wildfires, in turn, negatively impact the biological integrity of remnant native plant and animal populations and communities, water quality, and human life and property (Smith and Tunison, 1992; LaRosa et al., 2008). Invasive grass species typically recover rapidly following fire by resprouting and/or seedling recruitment (D'Antonio et. al. 2000, Kartawinata and Mueller-Dombois 1972; Tunison *et al.* 1994, 2001), perpetuating the cycle of increased fire and invasion known as the invasive grass/wildfire cycle (D'Antonio and Vitousek, 1992; Williams and Baruch, 2000). In order to protect remnant native species and communities, the invasive grass/wildfire cycle must be managed and, ultimately, eliminated. In order to do this, a much better understanding of the fuel, climatic, and fire behavior components of the invasive grass/wildfire cycle is needed. In particular, models that accurately predict the probability of ignition, rates of spread (ROS), and fire intensity are urgently needed to predict, control and manage wildfires in Hawaii.

Guinea grass, originally from Africa, currently has a pantropical distribution due to widespread introductions for livestock forage, and subsequent invasions into natural areas (D'Antonio and Vitousek, 1992; Portela et al., 2009). This problematic invader was introduced to Hawaii for cattle forage, became naturalized in the islands by 1871 (Motooka et al., 2003), and has altered flammability by increasing fuel loads and continuity (Chapter 2). Year-round high fine fuel loads with a dense layer of dead litter maintain a significant fire risk throughout the year in guinea grass dominated ecosystems (Chapter 3) Because guinea grass recovers quickly following disturbances (*i.e.* fire, land use change, etc.) and is competitively superior to native species (Ammondt and Litton, 2012; Ammondt et al., 2012), it now dominates a wide range of ecosystems (dry to wet) in Hawaii (Beavers, 2001) and throughout the tropics (Parsons, 1972; Williams and Baruch, 2000).

The spatial and temporal variability in guinea grass fuel loads in Hawaii has been well documented (Beavers, 2001; Wright et al., 2002). Live and dead fine fuel loads range spatially from 0.85 to 8.66 Mg ha^{-1} and 1.50 to 25.74 Mg ha^{-1}, respectively, and live and dead fuel moistures vary spatially by 250% and 54%, respectively. These values are similar to those reported for tall grass fuel loads in similar pastures throughout the tropics (Kauffman et al., 1998; Avalos et al., 2008; Portela et al., 2009). Potential fire behavior across this range of variability in fuels, however, has not been well quantified.

Fire modeling software programs such as BehavePlus (Andrews *et al.* 2005) were developed to simulate fire behavior and assist in predicting fire danger ratings, and are built around Rothermel's equations describing surface fire spread (Rothermel, 1972). These computer simulations predict fire behavior (*e.g.*, ROS and flame length) for fires burning in specific vegetation types, providing fire managers with a suite of decision-making tools. The model's predictive capability depends largely, however, on the accuracy of input variables such as fuel loads, fuel moisture, live:dead ratios, temperature, windspeed, and slope.

Standard fuel models have been developed for a wide range of ecosystem types to serve as input parameters in the BehavePlus modeling framework (Anderson, 1982; Scott and Burgan, 2005). However, these standard models do not accurately predict potential fire in all fuel types. As such, many custom fuel models have been developed for ecosystem types around the world, to better represent the potential for fire spread (Cheyette et al., 2008; Wu et al., 2011; Parresol et al., 2012).

Standard models do a very poor job of predicting fire behavior in tropical grasslands such as those found in Hawaii (Beavers, 2001). The unique fuels and climate of Hawaii likely require custom fuel models to accurately represent fire behavior in tropical grassland ecosystems. To address this need, Beavers (2001) created a custom fuel model for guinea grass for a narrow set of fuel conditions (mature and high load fuels at minimum fuel moistures), which has been moderately successful at accurately predicting fire behavior observed in guinea grasslands burning under extreme fire conditions on Oahu. When this model was tested outside these conditions, however, it underpredicted fire behavior (A. Beavers, personal comm.), indicating a critical need for a more robust fuel model that is applicable to a wider range of input data. Recent work has quantified the spatial and temporal variability in guinea grass fuel loads in Hawaii (Chapter 3), providing the data necessary for custom fuel modeling across a wide range of fuel loads and environmental conditions in this widespread tropical fuel type.

The objective of this study was to create a custom fuel model for guinea grass using field based measures of fuel characteristics and *in situ* climate data that accurately predicts the spread of fire through guinea grass dominated ecosystems in Hawaii, with applicability throughout the tropics. I hypothesized that this custom fuel model (GG2012) would perform better than either national tall grass fuel models (Grass 3, GR8, GR9) (Anderson, 1982; Scott and Burgan, 2005) or previous custom models for guinea grass in Hawaii (Beavers Grass 2) because *in situ* species-specific fuels data rather than generalized grass fuels parameters were used in its creation. To test this hypothesis, I used *in situ* fuels data collected on the Waianae Coast and North Shore areas of Oahu, Hawaii (Chapter 3) to develop a custom guinea grass fuel model (GG2012). This fuel model as well as three previous standard tall grass models and one previous custom guinea grass model were used along with fuel moisture and windspeed data recorded *in situ* to parameterize the BehavePlus fire behavior model to predict potential fire behavior across the range of conditions observed in the field. The three standard and two custom fuel models were then combined with fuel moisture and wind values measured at five fires in guinea grass ecosystems on Oahu, Hawaii to predict the behaviors of those fires, and these predictions were compared with observed fire behavior.

Methods

Custom Fuel Model creation

Fuels data used in the creation of a custom fuels model for guinea grass were collected on the North Shore and Waianae Coast areas of Oahu, Hawaii, USA between June 2008 and September 2010 (Chapter 3). Sites were located at Schofield Barracks, Makua Military Reservation, Waianae Kai Forest Reserve, and Dillingham Airfield to encompass the widest range of spatial variability in environmental conditions occurring on the leeward, fire-prone area of Oahu. All sites are dominated by guinea grass with some invasive *Leucaena leucocephala* (Lam.) de Wit in the area, although none was encountered in sample plots. Sample plots were selected based on continuous grass and limited overstory tree cover. For detailed site descriptions, see Chapter 3. BehavePlus (version 5.0.5) fire modeling software (Andrews et al., 2005) was used for all fire behavior simulations. All fuels data needed as input parameters in the BehavePlus 5.0 fire model were collected (see Chapter 3 for details), including live and dead fine fuels loads, live and dead fuel moisture, and fuel bed depth.

Fuel load and moisture parameters for the custom fuel model were derived as average values observed in the field. Two plots (Schofield Barracks MF1-1 and MF1-2) had lower fine fuel loads than other plots, which was likely an artifact of management pressure at the site (military training, repeated herbicide use, and vehicle traffic), and were not used in custom fuel model creation. For all remaining plots, the mean fine fuel loads for 1-hr, 10-hr, live herbaceous fuels, and fuel bed depth were used to parameterize the model. Height of the tallest grass blade was measured in each subplot, and fuel bed depth was recorded as 70% of the maximum fuel height (Burgan and Rothermel, 1984). Live and dead fuel heat contents were measured by bomb calorimetry (Hazen Research, Inc., Golden, Colorado, USA). Previously published values for dead fuel moisture of extinction of *M. maximus* (Beavers, 2001) were used. One-hour surface area to volume ratios were quantified using a LI-3100C portable leaf area meter (Li-Cor, Inc. Lincoln, Nebraska) and displacement in water.

The range of live and dead fuel moistures over one year (Chapter 3) were considered in model simulations. To capture the associated temporal variability in potential fire behavior as a result of changing fuel moisture, I ran model simulations with the minimum observed fuel moistures (Live, 48%; Dead 6%), 25th percentile (Live, 99%; Dead 13%), mean (Live, 160%; Dead 18%), 75th percentile (Live, 210%; Dead 20%), and maximum observed fuel moistures (Live, 294%; Dead 60%). Microclimate variables (air temperature, wind) were obtained from nearby RAWS weather stations. Twenty-ft wind speeds of 15 km hr^{-1} and 30 km hr^{-1}, which represent the average and extreme wind conditions observed at field sites, were used to simulate moderate and severe fire danger scenarios. A wind adjustment factor of 0.4 was used for all plots, to adjust the windspeed collected by the RAWS weather stations (20-ft wind speed) to that at the vegetation height (midflame wind speed) (Andrews et al., 2005). An average air temperature (22°C) was used for all simulations. Modeled fire behavior output consisted of maximum rate of spread (ROS) (m/min), fireline intensity (kW m^{-1}), and flame length (m).

Comparisons with previous fuel models

The new custom fuel model (GG2012) was compared to all prior fuel models which have been used in tall tropical grassland ecosystems including: NFFL Fuel Model 3 "Tall Grass" (Anderson 1982), Standard Model GR8 "High Load, Very Coarse, Humid Climate Grass" (Scott and Burgan 2005), Standard Model GR9 "Very High Load, Humid Climate Grass" (Scott and Burgan 2005), and the previous custom fuel model for guinea grass, Beavers Grass 2 (Beavers, 2001). Simulations for average fuel loads under each of the above fuel moisture scenarios (min, 25th percentile, mean, 75th percentile, max) were run for each grass fuel model.

Model validation and Statistical Analyses

Eleven prescribed fires occurred on August 15, 2000 for validation of the Beavers Grass 2 model (Beavers, 2001). Of these fires, only five were headfires, an important assumption of predictive fire modeling (Rothermel, 1972). Thus, these five headfires were the only fires used for fuel model validation comparisons. Due to military training, unexploded ordinance, and prohibitive costs of securing suppression resources, I was unable to do additional validation fires at this time. Model simulations using the custom GG2012 fuel model, as well as the previous four fuel models and the reported on site fuel moisture and weather conditions at the time of the burns, were run for each of the five prescribed headfires. Regression relationships between the predicted and observed ROS and flame lengths were examined. Specifically, the slope of each regression line and plots of the residuals were examined along with the root mean square error (RMSE) to determine model fit. The slope of the regression indicates whether the model predicts accurately throughout the range of the data, and the root mean square error (RMSE) is a measure of the difference between a model prediction and the observed value. An ideal model would have a low RMSE and slope near 1.0.

Results

Custom Fuel Model creation

The custom GG2012 fuel model was markedly different from prior tall grass fuel models, including the custom Beavers Grass 2 fuel model for guinea grass in Hawaii (Table 1). The 1-hour (dead fine) fuel component was higher (11.45 Mg ha^{-1}) in my fuel model than in any prior model (1.12-8.97 Mg ha^{-1}). Ten-hour dead fuels in the custom fuel model (2.86 Mg ha^{-1}) were similar to those from the GR8 and GR9 standard fuel models (2.24 Mg ha^{-1}), but lower than the custom Beavers Grass 2 fuel model (6.73 Mg ha^{-1}). The live fine fuel component in the custom GG2012 fuel model (3.77 Mg ha^{-1}) was lower than all other models explored (8.97-20.18 Mg ha^{-1}), except the NFFL standard fuel model 3, which has no live fine fuel component. As all of the compared models are grassland models, there was no woody fuel component. Surface area to volume ratios (SA:V) were higher in all standard models (49-59 cm^{-1}) than those measured *in situ* for guinea grass in Hawaii (34.5-39.3) (Chapter 3). Fuel bed depth for the custom GG2012 fuel model (78.2 cm) was also lower than the GR8 (122 cm) and GR9 (152.4 cm) standard models, but higher than the NFFL standard model 3 (76.2 cm) or the custom Beavers Grass 2 fuel model for guinea grass in Hawaii (57.3). Measured dead and live fuel heat content used in the new custom GG2012 fuel model was lower (16,282 and 16,747 kJ/kg, respectively) than the default value assumed by all prior fuel models used here (18,622 kJ/kg) (Table 1).

When all fire model simulations were run over the range of fuel moistures observed in the field (dead, 6-60%; live, 48-294%), the various grass fuel models resulted in quite different fire behavior parameters (Figures 1-3). NFFL standard model 3, the original tall grass model (Anderson, 1982), had a fairly low dead fuel input, with no live grass portion, giving predicted fire behavior that was consistently one of the fastest moving (ROS of up to 65.8 m min^{-1}; Figure 2), particularly under the higher windspeed scenario. Flame lengths in the NFFL standard model 3, however, were moderate (0-5.2 m) due to overall lower total fuel loads (Figure 1). GR8 and GR9 standard models (Scott and Burgan, 2005) predicted high intensity, fast moving fires (ROS up to 119.5 m min^{-1}) at the minimum fuel moistures (Figures 2 and 3), but all output parameters drop off to well below that of other models in all other moisture scenarios due to the large live fuel load input (Table 1). The previous custom fuel model for guinea grass in Hawaii, Beavers Grass 2 (Beavers, 2001), predicted lower intensity fires (ROS ≤16.7 m min^{-1}; flame lengths ≤5.9m) at low fuel moisture than any of the standard grass models, and fire behavior declined steadily with increasing live and dead fuel moisture (Figure 2). At the 75th percentile moisture scenario, the Grass 2 standard fuel model predicted ROS of 1.5-3.1 m min^{-1} and flame lengths of 1.4-2.0 m. The custom GG2012 fuel model showed a very similar pattern of declining fire behavior with increasing fuel moisture as the Grass 2 fuel model, but with ROS 79-207% higher than the Grass 2 fuel model, with greater differences at low fuel moistures (Figure 2). Flame lengths were consistently higher (9-71%) in the new custom fuel model than Grass 2 (Figure 1).

Model validation and Statistical Analyses

Comparisons of observed ROS and flame lengths (Beavers, 2001) with those predicted by the five fuel models, showed that while none of the models perfectly predicted fire behavior, the custom GG2012 fuel model presented here does improve on prior model predictions (Tables 2 and 3; Figures 4 and 5). Flame lengths were consistently overpredicted by GR8 and GR9 standard fuel models, and underpredicted by NFFL standard fuel model 3 Beavers Grass 2 and the new GG2012 fuel models (Figure 4). Regression results showed that all models had high R^2 values (≥0.94) and significant P-values (≤0.01). The slope of the regression line, however, is a better estimate of how well the model is predicting throughout the range of data, and an ideal model would have a high R^2, a low RMSE, and a slope near 1.0. The GR8 and GG2012 models had the lowest RMSE (1.7; Table 2), indicating the best fit between model predictions and observed flame lengths. However, the GR8 standard fuel model consistently overpredicted flame lengths (slope = 0.82), and the GG 2012 model underpredicted flame length (slope = 1.50) (Table 2, Figure 4).

Rate of spread was greatly overpredicted by all standard fuel models, particularly for higher intensity fires (Figure 5), with the GR9 standard fuel model again showing the greatest departures from observed fire behavior. Both custom models for guinea grass in Hawaii underpredicted ROS, but GG2012 was a moderate improvement over Beavers Grass 2. All fuel models had high R^2 values (≥0.94) and significant P-values (≤0.01) for ROS. Slope of the regression ranged from 0.22-0.41 for standard models (Table 3), indicating that ROS was less well predicted with more intense fire behavior (Table 3; Figure 5). While the custom GG2012 fuel model consistently underpredicted ROS, the slope (1.40) was closest to 1.0 and the RMSE was lowest (4.0), indicating that it predicted fire rate of spread most consistently and accurately across the range of data.

Discussion

Accurate prediction of potential fire behavior is critical in Hawaii and throughout the tropics, where invasive grasses, climate change, and increased anthropogenic ignition sources interact to alter fire regimes and threaten remnant native ecosystems and surrounding developed areas (D'Antonio andVitousek, 1992; Mack andD'Antonio, 1998; Williams andBaruch, 2000). With improved knowledge of expected fire behavior, land managers can make informed decisions on the pros and cons of prescribed fire, military live fire training, and human activities. Additionally, improved fire behavior estimates allow managers to better plan for adequate suppression resources in the event of a wildfire.

Standard fuel models, which were almost exclusively developed outside of the tropics, are typically based upon very different assumptions than the conditions that I measured in the field (Anderson, 1982; Scott andBurgan, 2005). Thus, it is not surprising that the standard fuel models explored here did not accurately predict fire behavior in guinea grass dominated tropical ecosystems in Hawaii. The original Grass 3 standard fuel model (Anderson, 1982) was intended for grasslands and prairies where total fuel loads are <7 Mg ha^{-1}. Fuel loads in tropical ecosystems have been shown to far exceed this threshold (Kauffman et al., 1998; Avalos et al., 2008; Portela et al., 2009), and guinea grass fuel loads in Hawaii have been measured at much higher levels as well (11-30 Mg ha^{-1}; Chapter 3). The GR8 and GR9 standard fuel models were intended for tall, humid climate grasslands with high (16.4-20.2 Mg ha^{-1}) live herbaceous fuel loads (Scott and Burgan, 2005), which exceed the average live fuel load measured in guinea grass ecosystems in Hawaii by 434-535% (3.8 Mg ha^{-1}; Chapter 3). Because these are dynamic models, a portion of the live fuel load is transferred to the dead fuel category as fuel moisture decreases (Scott andBurgan, 2005). This modeled 'curing' is responsible for low intensity fire behavior predictions at high fuel moisture and extreme fire behavior predictions at low fuel moisture. These standard fuel models do not represent guinea grass fuels well, as previous data has shown that guinea grass fuel loads maintain a large dead component year-round, with a much lower live grass fuel load (Chapter 3).

Prior custom fuel model work for guinea grass in Hawaii dramatically improved ability to predict fire behavior in these grasslands (Beavers, 2001). However, because this custom fuel model was intended for use only in mature guinea grass stands under the lowest moisture conditions (i.e., conditions conducive to extreme fire behavior), it cannot readily be extrapolated to larger spatial and temporal scales where fuel conditions vary dramatically (Chapter 3). With the recent collection of fuels data over a large range of spatial and temporal variability in guinea grass (Chapter 3), adequate data are now available to expand on prior custom fuel modeling work. With the limited actual fire behavior data available (n=5), it is difficult to quantify the conditions under which these custom fuel models for guinea grass in Hawaii accurately predict fire behavior, and where they need refinement. The wide range of fuel loads and fuel moistures measured in Hawaii (Chapter 3) may justify having multiple custom fuel models (low, moderate, and high fuel loads, for example) to more accurately represent this fuel type and the wide range of environmental conditions where it occurs. Multiple fires to validate each of these custom fuel models, however, would be critical to ensure their reliability in predicting fire behavior.

Accurate prediction of fire behavior is critical for management not only in Hawaii, but throughout tropical grasslands where native species, ecosystem function, and human life and property are at risk from frequent anthropogenic ignitions. Models that accurately predict the behavior of a current or potential fire guide management decisions in several important ways. First, when an actual fire occurs, knowledge of expected flame lengths and ROS can help managers plan for the fire suppression resources needed to control the fire. Similarly, prescribed fires, along with human activities likely to result in unintended fires (e.g., military live fire training), can be planned when danger of fire escaping the desired burn area is low, and the fire personnel and resources on site are able to contain any unexpected spot fires or changes in weather (*i.e.* shift in wind speed or direction). Finally, custom fuel models can also be used to simulate the difference in expected fire behavior due to fuels management treatments such as grazing (Evans et. al., unpublished data), herbicide and mechanical fuels reduction treatments (Ansari et al., 2008), and restoration activities (Ammondt et al 2012, Chapter 3).

As hypothesized, the custom fuels model for guinea grass based on field data across a wide range of spatial and temporal variability outperformed national standard fuel models (Anderson, 1982; Scott and Burgan, 2005), as well as a previous custom fuel model for guinea grass ecosystems in Hawaii (Beavers, 2001), when tested against limited available observed fire behavior data. However, because of the large range of variability in fuel loads and moistures observed for guinea grass in Hawaii (Chapter 3), I believe that multiple validated models may be needed to more precisely describe expected fire behavior in ecosystems dominated by this species.

Table 1. Input parameters for BehavePlus fire simulations in guinea grass dominated ecosystems on Oahu, Hawaii.

BehavePlus Input	NFFL Fuel Model 3[a]	Standard GR8[b]	Standard GR9[c]	Grass 2 (Custom)[d]	GG2012 (Custom)
1-hr fuel load (Mg ha^{-1})	6.75	1.12	2.24	8.97	11.45
10-hr fuel load (Mg ha^{-1})	0	2.24	2.24	6.73	2.86
Live herb fuel load (Mg ha^{-1})	0	16.36	20.18	8.97	3.77
Live woody fuel load (Mg ha^{-1})	0	0	0	0	0
1-hr SA/Vol (cm^{-1})	49.21	49	59	39.3	35
Live herb SA/Vol (cm^{-1})	49.21	43	52	36.1	34.5
Fuel bed depth (cm)	76.2	122	152.4	57.3	78.2
Dead fuel moisture of extinction (%)	25	30	40	40	40
Dead fuel heat content (kJ/kg)	18622	18622	18622	18622	16282
Live Fuel heat content (kJ/kg)	18622	18622	18622	18622	16747

[a]"Tall Grass" Anderson 1982; [b] "High Load, Very Coarse, Humid Climate Grass" (Scott and Burgan 2005); [c]"Very High Load, Humid Climate Grass" (Scott and Burgan 2005); [d]"Grass 2" (Beavers 2001)

Table 2. Summary of flame length regression statistics for three standard and two custom fuel models for guinea grass in Hawaii. The slope of the regression indicates whether the model predicts accurately throughout the range of the data, and the root mean square error (RMSE) is a measure of the difference between a model prediction and the observed value. An ideal model would have a low RMSE and slope near 1.0.

Model	RMSE	Slope
NFFL Model 3	2.1	1.57
Standard GR8	1.7	0.82
Standard GR9	4.2	0.59
Grass 2	1.9	1.61
GG2012	1.7	1.50

Table 3. Summary of rate of spread regression statistics for three standard and two custom models for guinea grass. The slope of the regression indicates whether the model predicts accurately throughout the range of the data, and the root mean square error (RMSE) is a measure of the difference between a model prediction and the observed value. An ideal model would have a low RMSE and slope near 1.0.

Model	RMSE	Slope
NFFL Model 3	22.8	0.41
Standard GR8	26.4	0.38
Standard GR9	54.2	0.22
Grass 2	7.7	2.40
GG2012	4.0	1.40

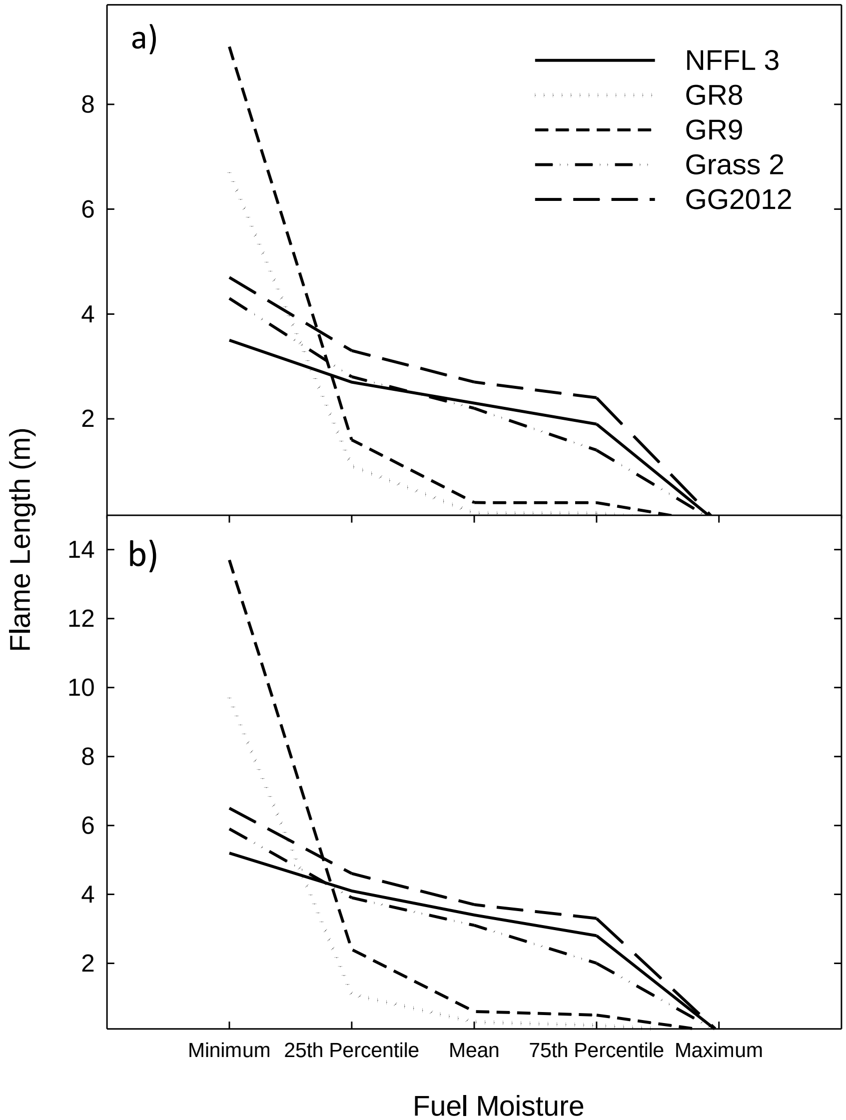

Figure 1. Predicted flame lengths for 3 three standard (NFFL, GR8, and GR9) and two custom (Grass 2 and GG 2012) fuel models under a range of fuel moisture conditions at windspeeds of a) 15 kph and b) 30 kph. Moisture scenarios are based on *in situ* fuel moisture conditions in guinea grass sites on Oahu, Hawaii: Minimum (Live fuel moisture 48%, Dead fuel moisture 6%), 25th percentile (Live 99%, Dead 13%), Mean (Live 160%, Dead 18%), 75th percentile (Live 210%, Dead 20%), and Maximum (Live 294%, Dead 60%).

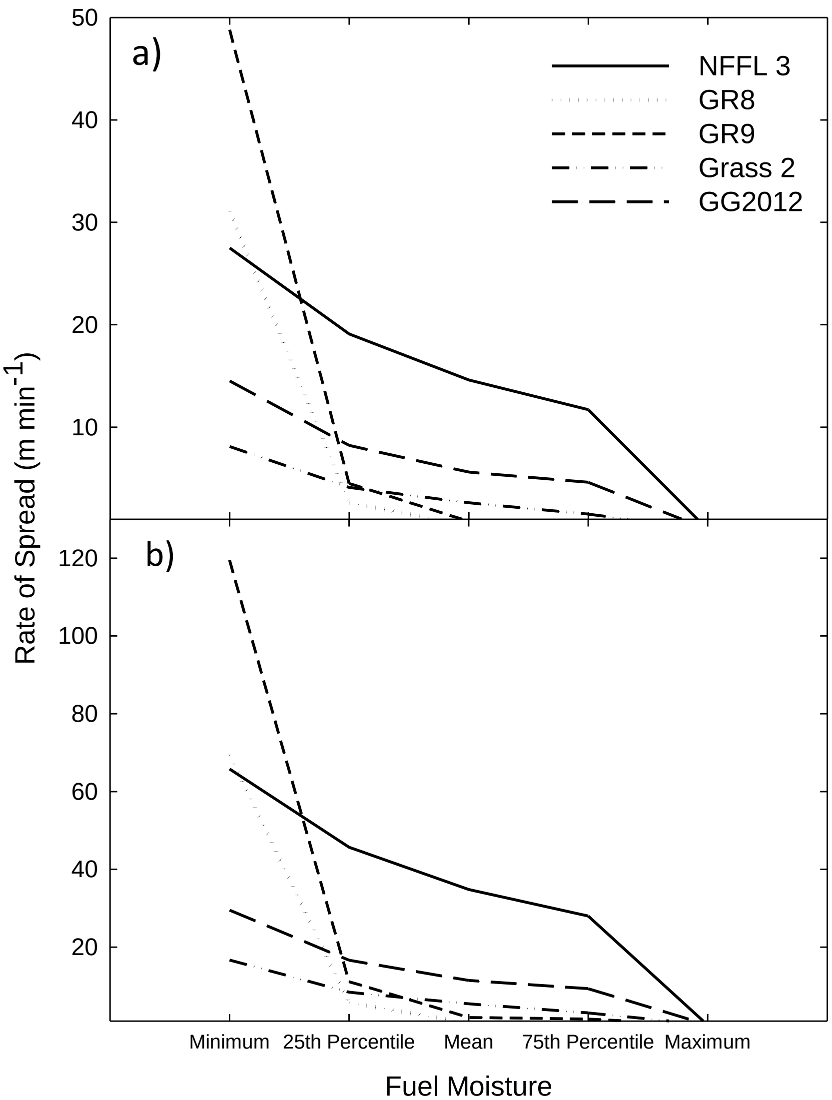

Figure 2. Predicted rates of spread for 3 three standard (NFFL, GR8, and GR9) and two custom (Grass 2 and GG 2012) fuel models under a range of fuel moisture conditions at windspeeds of a) 15 kph and b) 30 kph. Moisture scenarios are based on *in situ* fuel moisture conditions in guinea grass sites on Oahu, Hawaii: Minimum (Live fuel moisture 48%, Dead fuel moisture 6%), 25th percentile (Live 99%, Dead 13%), Mean (Live 160%, Dead 18%), 75th percentile (Live 210%, Dead 20%), and Maximum (Live 294%, Dead 60%).

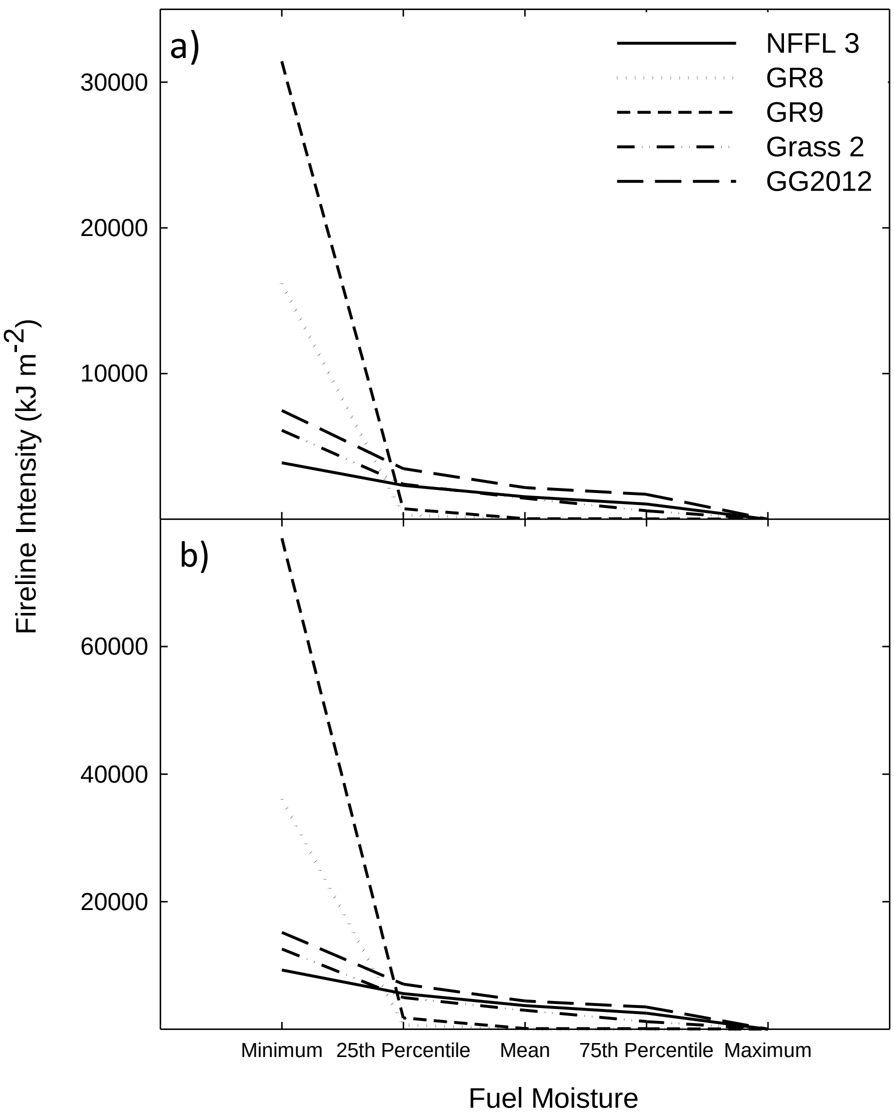

Figure 3. Predicted fireline intensity for 3 three standard (NFFL, GR8, and GR9) and two custom (Grass 2 and GG 2012) fuel models under a range of fuel moisture conditions at windspeeds of a) 15 kph and b) 30 kph. Moisture scenarios are based on *in situ* fuel moisture conditions in guinea grass sites on Oahu, Hawaii: Minimum (Live fuel moisture 48%, Dead fuel moisture 6%), 25th percentile (Live 99%, Dead 13%), Mean (Live 160%, Dead 18%), 75th percentile (Live 210%, Dead 20%), and Maximum (Live 294%, Dead 60%).

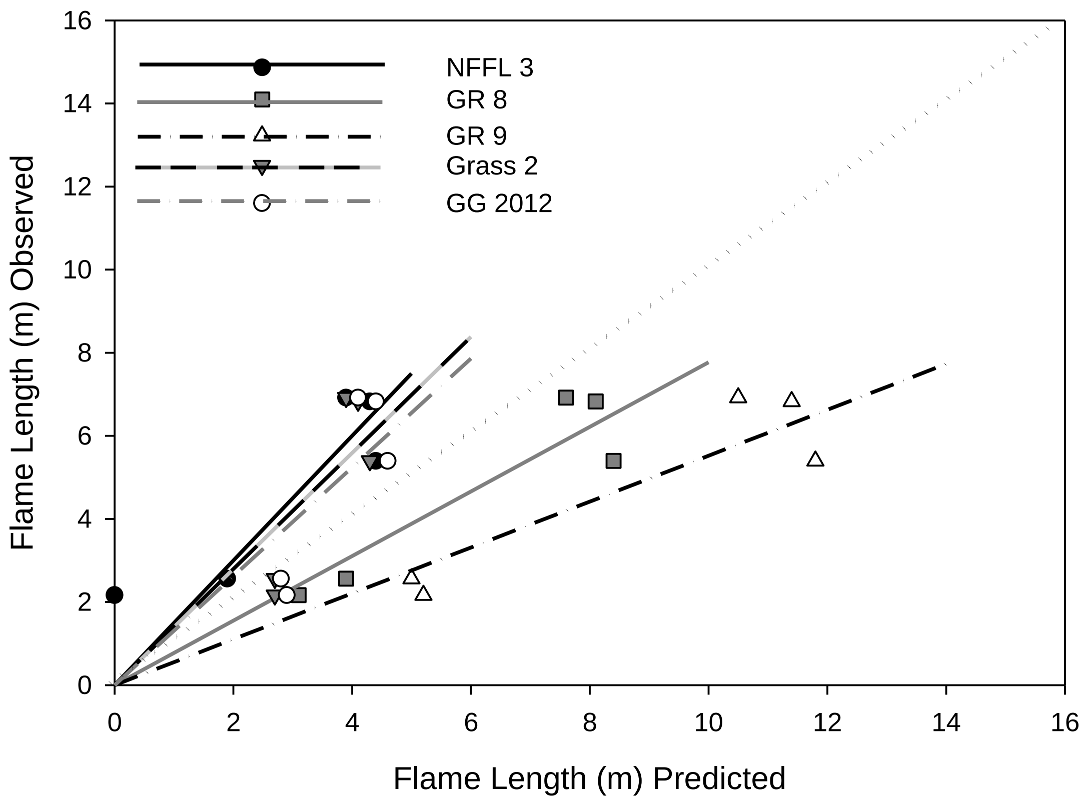

Figure 4. Observed vs. predicted flame length in guinea grass dominated ecosystems in Hawaii for three standard (NFFL, GR8, and GR9) and two custom (Grass 2 and GG 2012) fuel models. The dotted diagonal line represents the 1:1 line. Data points and regression lines that fall above the 1:1 line have been under-predicted by the model, and data points that fall below the 1:1 line have been over-predicted by the model.

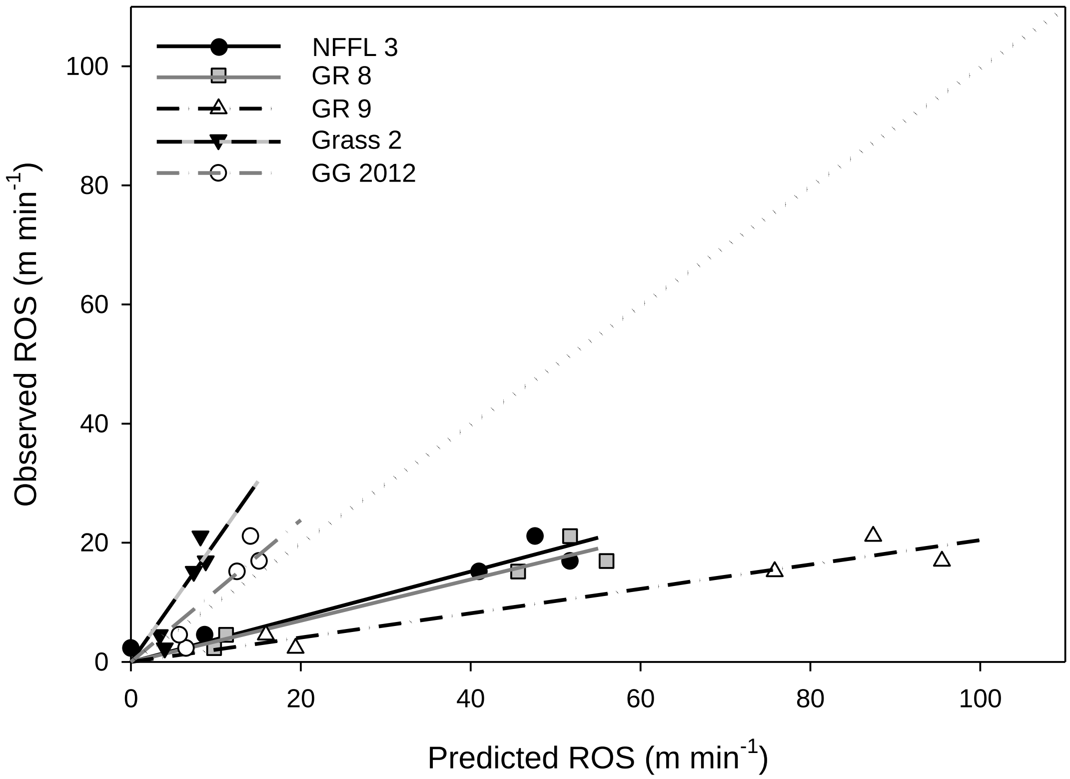

Figure 5. Observed vs. predicted rate of spread (ROS) in guinea grass for three standard (NFFL, GR8, and GR9) and two custom (Grass 2 and GG 2012) fuel models. The dotted diagonal line represents the line of perfect agreement. Data points that fall above and to the left the line have been under-predicted by the model, and data points that fall below and to the right of the line have been over-predicted by the model.

CHAPTER 5. IMPROVED PREDICTION OF LIVE AND DEAD FUEL MOISTURE IN INVASIVE *MEGATHYRSUS MAXIMUS* GRASSLANDS IN HAWAII WITH MODERATE RESOLUTION IMAGING SPECTRORADIOMETER (MODIS)

Abstract

The synergistic impacts of nonnative grass invasion and frequent anthropogenic fire threaten endangered species and native ecosystems, and adjacent land throughout the tropics. Fire behavior models can be an effective tool in fire prevention and management. However, current models do not accurately predict fire ignition or behavior in Hawaii. Specifically, current models do a poor job at predicting fuel moisture, which is a key driver of fire. To address this shortcoming, I developed empirical models to predict real-time live and dead fuel moisture contents in nonnative grasslands in Hawaii dominated by *Megathyrsus maximus* from Terra-MODIS NDVI and EVI2 vegetation indices. MODIS-based predictive models for live fuel moisture were moderately effective (R^2= 0.46), but 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). 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.

Introduction

The introduction and spread of invasive species is a leading cause of biodiversity loss in Hawaii (Loope, 2004; Loope et al., 2004; Hughes and Denslow, 2005). Many nonnative plant invaders promote more frequent and intense fire regimes, particularly nonnative grasses, and the synergistic interactions of fire and these invasive grasses pose serious threats to the biological integrity and sustainability of tropical ecosystems worldwide (Foxcroft et al., 2010; Miller et al., 2010; Pysek et al., 2012). The invasive grass/fire cycle – a positive feedback between frequent anthropogenic fire and nonnative grass invasion – is now a reality in many landscapes formerly occupied by native woody communities. This feedback has dramatically increased fire frequencies, often with severe consequences for native plant assemblages (D'Antonio and Vitousek, 1992). This scenario is particularly evident in areas dominated by guinea grass (*Megathyrsus maximus* [Jacq.], previously *Panicum maximum* and *Urochloa maxima* [Jacq.]) in Hawaii, as well as throughout the tropics. Large portions of the landscape that were once dominated by diverse tropical plant communities are now covered primarily by flammable invasive grasses that pose significant fire threats to remnant native plant communities and adjacent human-dominated areas.

Fire modeling programs such as BehavePlus (Andrews et al., 2005) and the National Fire Danger Rating System (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 (Chapter 3). 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).

Chuvieco *et al.* (2002) examined the potential to use imagery from the Landsat Thematic Mapper (TM) to estimate fuel moisture content in live Mediterranean fuels, and found a strong relationship between short-wave infrared (SWIR) reflectance and live fuel moisture content for grassland (r^2= 0.84) and shrubland (r^2= 0.74) ecosystems. While these relationships highlight the potential for predicting live fuel moisture from remotely sensed imagery, the temporal resolution of the TM sensor (~4 images/year) is too coarse to make it a useful tool for fire managers. Terra-Moderate Resolution Imaging

Spectroradiometer (MODIS) imagery, on the other hand, has a daily temporal resolution which could be more practical for informing fire prevention and management activities. Hao and Qu (2007) described an algorithm for predicting live fuel moisture from multiple MODIS bands, and demonstrated high correlation between predicted and estimated live fuel moisture content (r^2= 0.77) across several ecosystem types in Georgia, USA. Recently, Caccamo et al. (2011) evaluated the use of vegetation indices derived from MODIS imagery to monitor fuel moisture in shrubland, heathland, and sclerophyll forest ecosystems in south-eastern Australia. They found that the MODIS-derived vegetation indices had far stronger relationships with fuel moisture (R^2= 0.69) than the previously used Keetch-Byram drought index (KDBI; R^2= 0.15).

Vegetation indices have been highly successful at relating vegetation properties (e.g., cover, phenology, and composition) to spectral signatures. The Normalized Difference Vegetation Index (NDVI) (Huete et al., 2009) is commonly used in a wide range of remote sensing applications and has been shown to be a good predictor of vegetation characteristics because chlorophylls *a* and *b* in green vegetation strongly absorb light in the red regions of the electromagnetic spectrum, and plant cell walls strongly absorb light in the near infrared region (Glenn et al., 2008). Vegetation indices derived from satellite data, therefore, are good indices of canopy greenness, which in turn reflects not only chlorophyll content but also vegetation moisture content. NDVI utilizes a ratio of the difference in reflectance (ρ) in the near infrared (NIR) and red spectral bands to their sum as follows:

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \quad (1)$$

NDVI has been shown to be important at measuring vegetation change over time (Jensen, 2007) and has been applied in many types of vegetation studies such as assessment of net primary productivity (Rasmussen, 1998), drought monitoring (Unganai and Kogan, 1998), and leaf area index (Wang et al., 2005). NDVI, however, has several limitations. Soil color, atmospheric effects and cloud cover greatly diminish the accuracy of NDVI values, and this index tends to saturate at high vegetative cover, making it less sensitive to differences in vegetation as cover increases.

Because of the limitations of NDVI, the Enhanced Vegetation Index (EVI) was developed. EVI is a modified NDVI which adjusts for soil color and atmospheric aerosol scattering (Jensen, 2007), and has improved sensitivity to high biomass areas. This improved signal increases the sensitivity of EVI (relative to NDVI) to change in vegetation (i.e. greenness).

$$EVI = G \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + C_1 \rho_{red} - C_2 \rho_{blue} + L} \tag{2}$$

where G is a gain factor set at 2.5, C_1 and C_2 are coefficients derived from the use of the blue band to correct for aerosol influences in the red band, and are set at 6.0 and 7.5, respectively (Jensen, 2007; Jiang et al., 2008). L is a canopy background adjustment term, set at 1.0 (Jensen, 2007). EVI is now a standard NASA product and is currently distributed for free by the USGS. Easy access to this index makes the MODIS EVI product incredibly useful and accessible to researchers and land managers without advanced training in processing remotely sensed data.

The scope of many remote sensing applications (i.e. vegetation, climate, and land cover change) is greatly broadened by the use of historical data, and the development of a two-band Enhanced Vegetation Index (EVI2) using just the NIR and red spectral bands allows researchers to extend the EVI record back over 30 years (Jiang et al., 2008). EVI2 was derived by retaining the NIR and red reflectances from the EVI equation as well as the gain factor (G=2.5) and the background canopy adjustment term (L=1). The blue band is removed, and a single coefficient C_1 becomes 2.4, giving Equation 3:

$$EVI2 = G \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + 2.4 \rho_{red} + L} \tag{3}$$

Other, less commonly used indices have also been shown to have strong relationships with vegetation moisture. Visible Atmospherically Resistant Index (VARI) correlates well spatially and temporally ($0.79 \leq r^2 \leq 0.94$) with fuel moisture content in chaparral ecosystems (Stow et al., 2005; Roberts et al., 2006). :

$$VARI = \frac{\rho_{green} - \rho_{red}}{\rho_{green} + \rho_{red} - \rho_{blue}} \tag{4}$$

NDWI (Normalized Difference Water Index) (Gao, 1996) was shown to have high correlations with fuel moisture content in chaparral and oak woodland ecosystems (Dennison et al., 2005; Roberts et al., 2006). NDWI, a NIR based index, is shown in equation 5:

$$NDWI = \frac{\rho_{NIR1} - \rho_{NIR2}}{\rho_{NIR1} + \rho_{NIR2}} \tag{5}$$

NDII (Normalized Difference Infrared Index) was shown in simulation modeling to be related to surface moisture content (Hunt and Yilmaz, 2007), but has not been evaluated extensively for its applicability to fuel moisture modeling. NDII uses NIR and short-wave infrared (SWIR) spectral bands as shown in equation 6:

$$NDII = \frac{\rho_{NIR1} - \rho_{SWIR1}}{\rho_{NIR1} + \rho_{SWIR1}} \tag{6}$$

Relative greenness (RGRE) (Kogan 1990) is a variation of NDVI using the maximum and minimum values over a given time period. It was developed to account for value changes within the pixel due to climate dynamics. The RGRE index has been used by fire managers as an estimate of fuel moisture content of live vegetation (Chuvieco et al. 2002):

$$RGRE = \frac{NDVIi - NDVI(\min)}{NDVI(\max) + NDVI(\min)} x100 \tag{7}$$

where *NDVIi* is the NDVI value at time period *i*, *NDVI* (min) is the minimum index value over the study period, and *NDVI* (max) is the maximum NDVI value over the study period. Using Landsat data, Chuvieco (2002) proposed the use of an integral of reflectances in the SWIR and visible bands and found strong correlations (r= 0.91) with fuel moisture contents in Mediterranean grasslands. The integral multiplies the reflectances of the visible and SWIR bands by the bandwidths:

$$Integral = 0.050\,\boldsymbol{\rho}_1 + 0.020\,\boldsymbol{\rho}_3 + 0.020\,\boldsymbol{\rho}_4 + 0.024\,\boldsymbol{\rho}_6 + 0.040\,\boldsymbol{\rho}_{7.} \tag{8}$$

Remotely sensed MODIS products are available from the NASA Earth Observing System Data and Information System (http://reverb.echo.nasa.gov/reverb/). Daily reflectance values are available as well as 8-day composite reflectance values. The 8-day composites include the best value for each pixel for an 8 day range, giving improved data quality but coarser temporal resolution. Additionally, NASA makes available pre-processed 16-day EVI and NDVI composites, as well as 16-day reflectance composites. Because these data sets are easily accessible, it would be an extremely valuable tool for land managers to be able to utilize pre-processed vegetation indices to predict time- and site-specific fuel moisture, which could then be used to potentially greatly improve fire models in Hawaii and throughout the tropical Pacific.

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 primary objective of this research was to 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. Specific hypotheses included: *(i)* 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; (*ii*) because live and dead fuel moisture are closely correlated (Chapter 3), I also expect moderate relationships between vegetation indices and dead fuel moisture content; *(iii)* 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 at the study sites; and *(iv)* 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 (Chapter 3). To test these hypotheses, I collected *in situ* live and dead fuel moisture content from three guinea grass dominated ecosystems biweekly for one year on the Island of Oahu, and examined relationships between these *in situ* data and vegetation indices derived from MODIS reflectance data.

Methods

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 (Figure 1). All sites are dominated by guinea grass with some invasive *Leucaena leucocephala* (Lam.) de Wit in the overstory. Dillingham Ranch is located at 5 m.a.s.l., with a mean annual precipitation (MAP) of 851 mm (Giambelluca et al., 2011) and mean annual temperature(MAT) of 24ºC (T. Giambelluca, *unpub. data*). Soils at Dillingham Ranch are in the Kawaihapai series (fine-loamy, mixed, superactive, isohyperthermic Cumulic Haplustolls), which are well drained soils formed in alluvium derived from basic igneous rock. At Schofield Barracks (297 m.a.s.l.; MAP = 1000 mm; MAT = 22ºC), soils are in the Kunia series (fine, parasesquic, isohyperthermic Oxic Dystrustepts) which formed in alluvium weathered from basalt rock (Table 1). At 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.

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 for these 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. I 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 reflectance 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). While there were 116 data points corresponding to *in situ* fuel moisture measurements, only 62% of them (N= 72) could be used in the analysis of models including WIMS data due to sensor or data transmission failure.

Statistical Analysis

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 for regression analyses. All independent variables that were significantly correlated with a given dependent variable were included in multiple linear regressions both individually and in all possible subset combinations to identify the most effective 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 best predictive relationships between all available fuel moisture predictors and *in situ* measured live and dead fuel moisture at each temporal scale. The predicted R^2 for each model was used as the criterion for selection. I was 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, I 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.

Results

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 2).

MODIS-based fuel moisture correlations

Vegetation indices calculated from daily MODIS data were also dynamic (Figure 2) and none were correlated with live, dead, or litter fuel moisture (Table 1; Figure 2), 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 3) 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 1). 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 1; Figure 3). 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 2), 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 3). 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; Table 3) 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 2) and dead fuel moisture (R^2 = 0.19; R^2_{pred} = 0.12; p=0.002; Table 3) 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 3) than MODIS-derived predictions (Table 2). 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 3; Figure 4). KDBI was an even poorer predictor of both live (R^2 = 0.06; R^2_{pred} = 0.01; p=0.050; Table 2) and dead (R^2 = 0.01; R^2_{pred} = 0.00; p=0.477) fuel moisture (Table 3).

Hybrid models (containing both MODIS and WIMS components) were generally more effective predictors of *in situ* fuel moisture than either MODIS or WIMS models alone (Table 2). The most effective 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 5), 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 3; Figure 6).

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.

Discussion

Overall, these results show that MODIS-based vegetation indices are better predictors of *in situ* fuel moisture content than currently used WIMS-based models for nonnative *M. maximus*-dominated grasslands in Hawaii. These results 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 the Coastal Plains of Georgia, USA (r =0.57-0.96) (Hao and Qu, 2007). While my 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 (Chapter 3), 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. I hypothesized that vegetation indices would be stronger predictors of live than dead fuel moisture, but expected a better model than obtained for dead fuel moisture, as both live and dead fuel moistures change seasonally with precipitation events (Chapter 3). 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 load (Kauffman et al., 1998), and typically play a predominant role in driving fire behavior. Despite the limitation of using MODIS-derived products to predict dead fuel moisture content in these ecosystems, these results show that the current WIMS-based prediction systems (NFDRS, KDBI), which are commonly used in fire management today in Hawaii, do an even poorer job of predicting dead fuel moisture content.

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 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), limiting accurate moisture prediction to small areas near RAWS towers. Further, sensors on weather towers frequently are inoperable or have sensors that have not been properly calibrated and, thus, commonly transmit inaccurate data which requires a thorough quality assurance protocol – 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 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} =0.41) over the MODIS-based model (R^2_{pred} =0.40) 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 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. My hypothesis that daily MODIS data would be the best predictor of fuel moisture, however, was not supported by my data. Instead, the best MODIS-only predictive models for both live and dead fuel moisture were developed using the 16-day composite data. I 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.

I hypothesized that EVI would be the strongest predictor of fuel moisture because previous work has shown it to perform well in areas of high biomass (Jensen, 2007), which was only partially supported by my data. The best overall model (hybrid) for live fuel moisture prediction incorporated 8-day composite EVI data, but the best MODIS-only models utilized NDVI and EVI2 vegetation indices. Overall, EVI, NDVI and EVI2 significantly outperformed all other types of vegetation indices explored.

In summary, this research evaluated the utility of MODIS-based vegetation indices to accurately predict fuel moisture content. These results demonstrate that remote sensing tools may improve current methods for real-time fuel moisture estimation in tropical grasslands. In addition, the models presented in this paper can be directly used by fire managers to improve real time moisture prediction in guinea grass dominated vegetation on leeward Oahu.

Table 1. Pearson correlation coefficients (*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 images						
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 composites						
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 2. 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 models. Bold font indicates most effective 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 3. 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

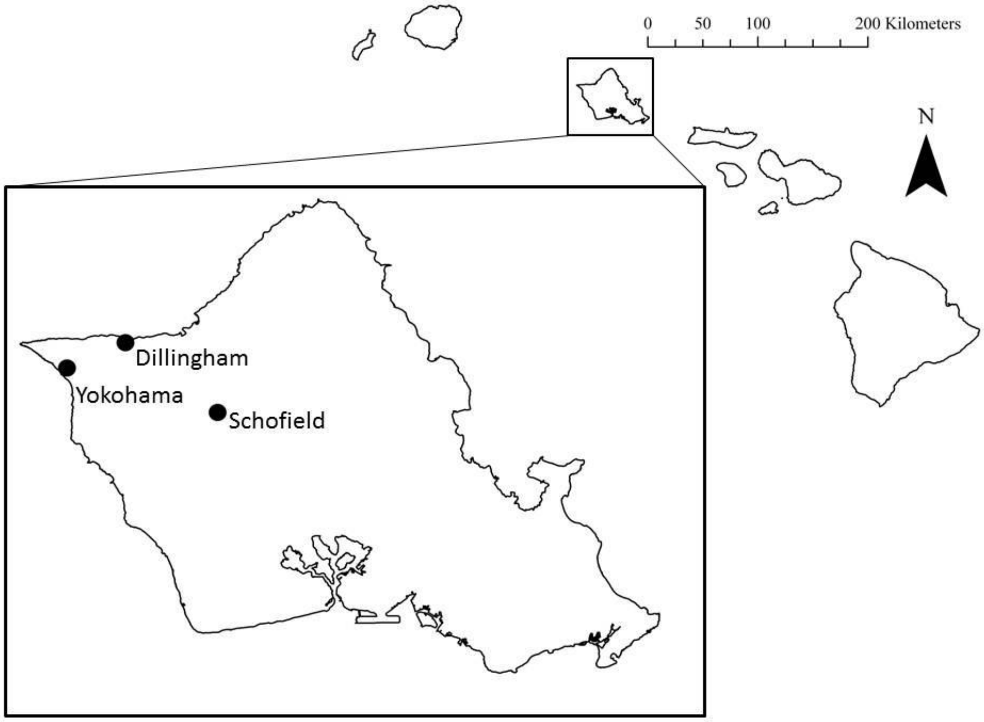

Figure 1. Location of sites for *in situ* live and dead fuel moisture sampling on the Waianae Coast and North Shores of Oahu, Hawaii.

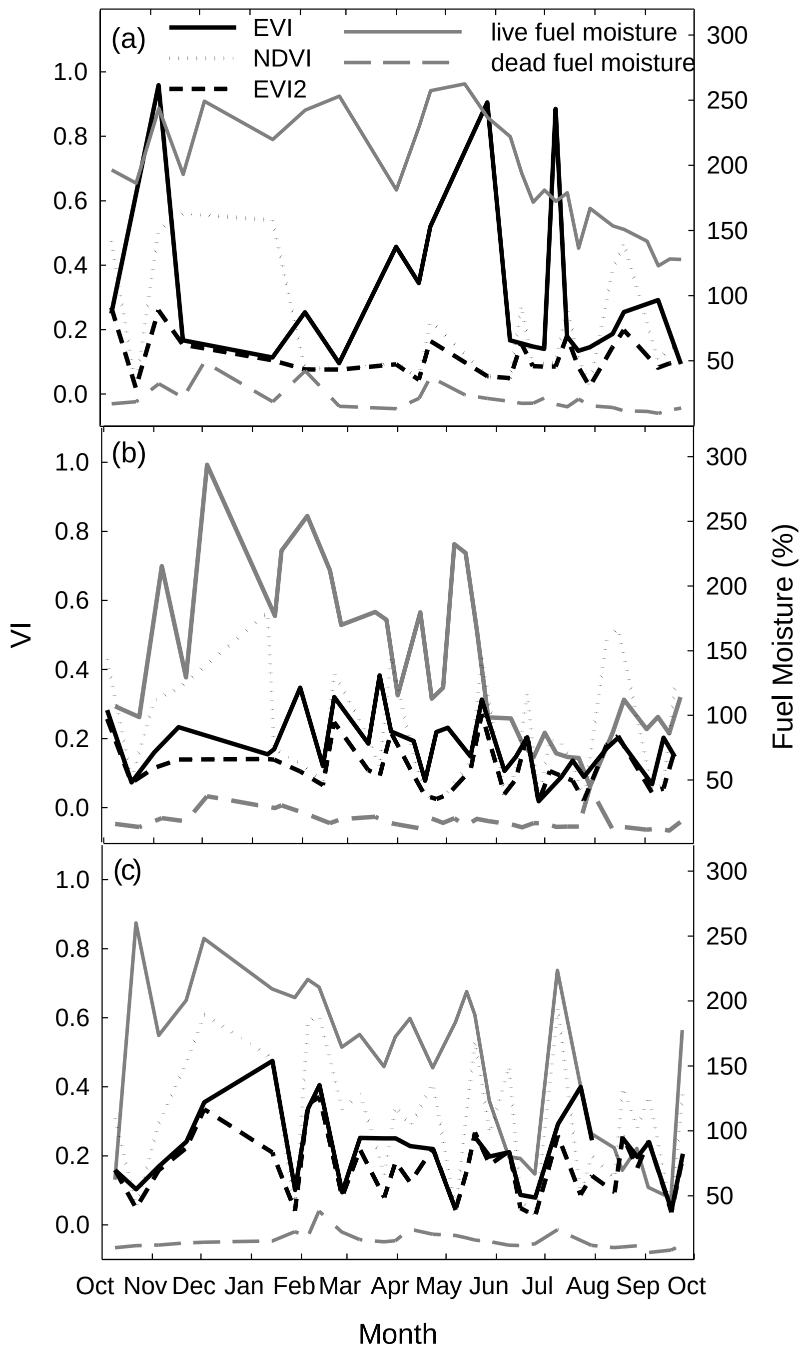

Figure 2: Temporal trends of *in situ* live and dead fuel moisture and daily MODIS-derived vegetation indices (VI) for nonnative invasive guinea grass ecosystems at (*a*) Schofield Barracks, (*b*) Dillingham Ranch, and (*c*) Yokohama State Park on Oahu, Hawaii from October 2009 – October 2010. VI's (NDVI, EVI, and EVI2) are shown by black lines, and live (solid) and dead (dashed) fuel moisture is shown in grey.

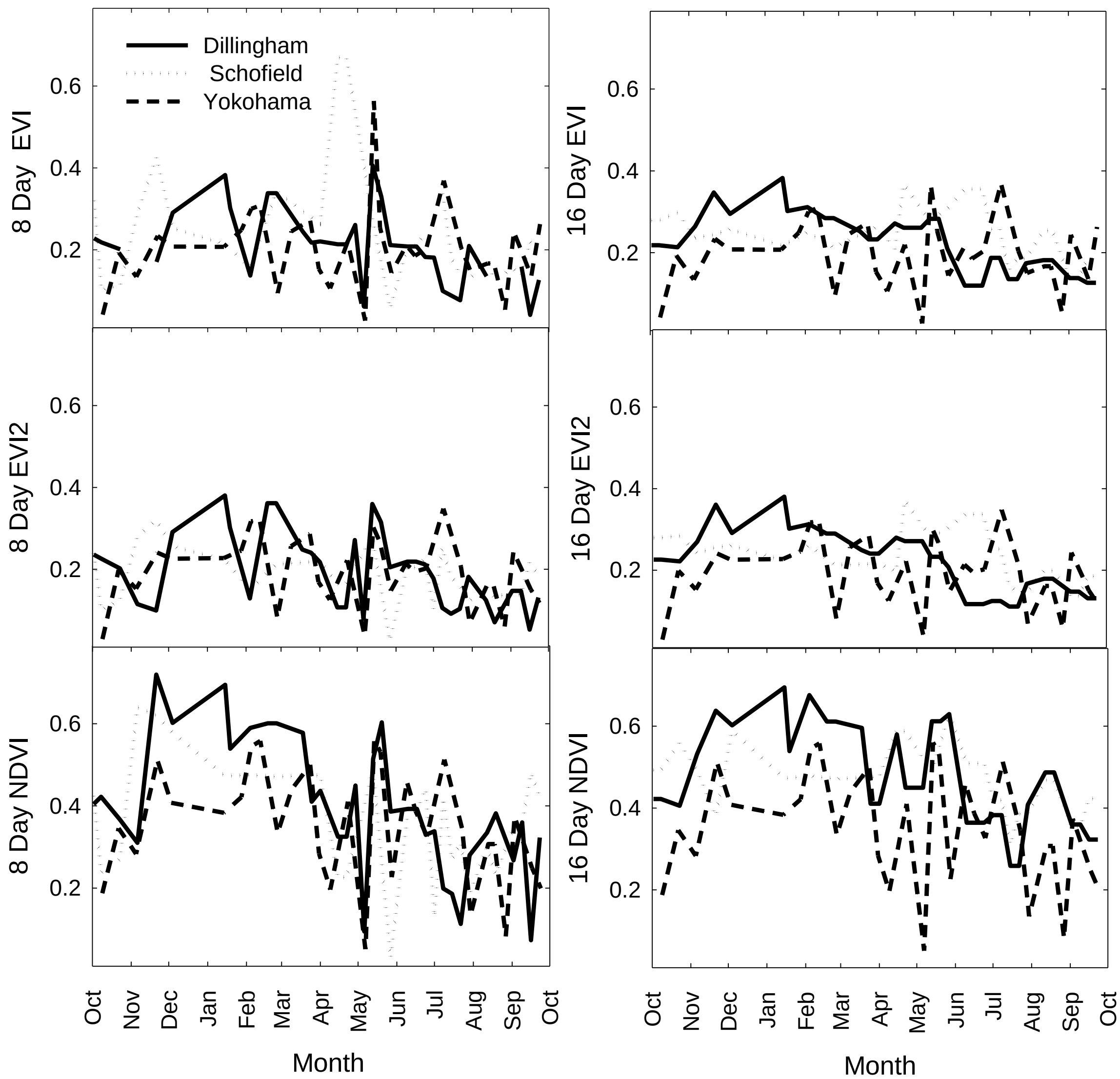

Figure 3: Temporal trends in 8-day composite and 16-day MODIS-derived vegetation indices (VI) for nonnative invasive guinea grass ecosystems at Schofield Barracks, Dillingham Ranch, and Yokohama State Park on Oahu, Hawaii from October 2009 – October 2010.

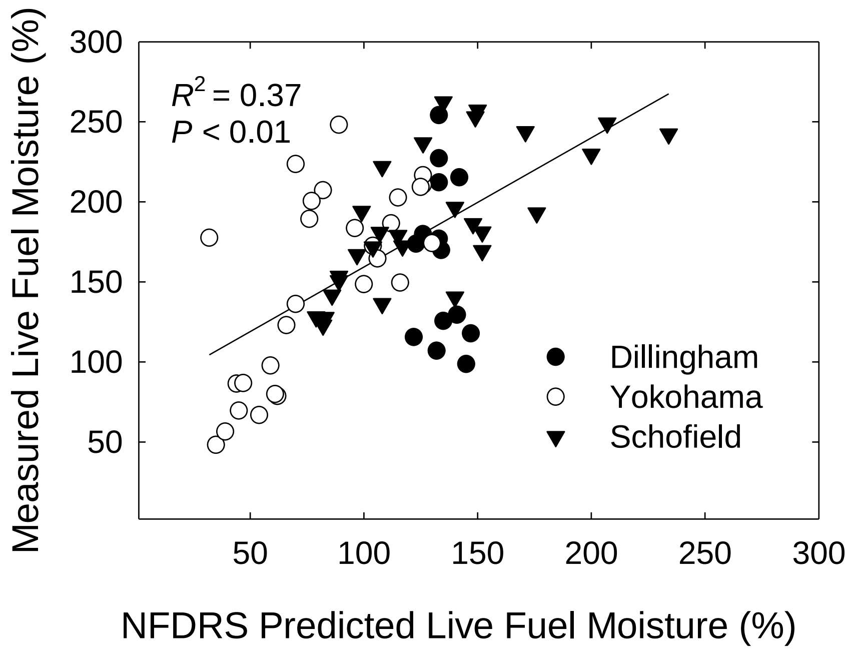

Figure 4: NFDRS system of live fuel moisture prediction (x-axis) vs. *in situ* live fuel moisture (y-axis) measurements.

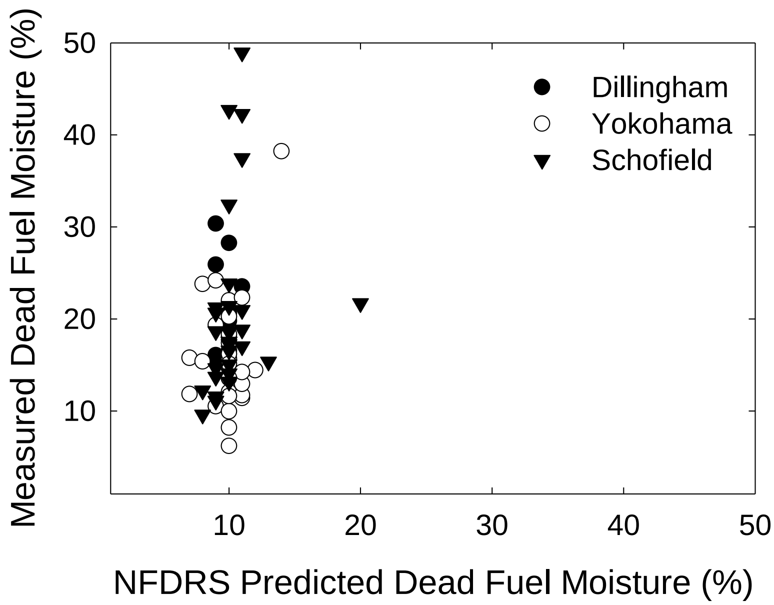

Figure 5: NFDRS system of dead fuel moisture prediction (x-axis) vs. *in situ* dead fuel moisture (y-axis) measurements.

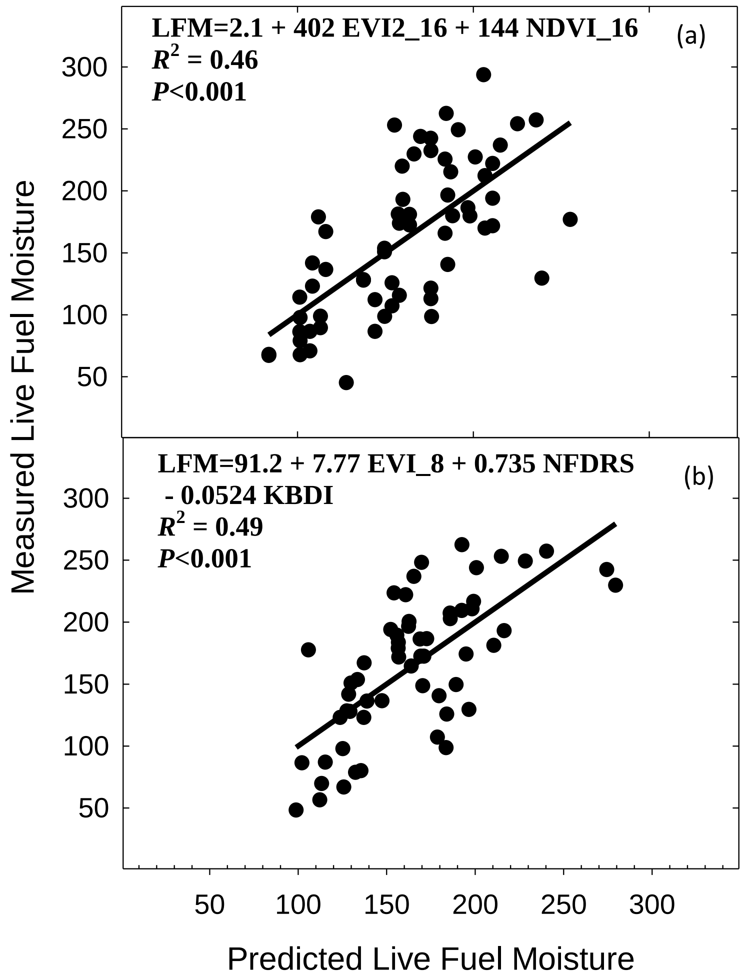

Figure 6: Live fuel moisture prediction (x-axis) using a) MODIS vegetation index and b) Hybrid models vs. *in situ* live fuel moisture (y-axis) measurements.

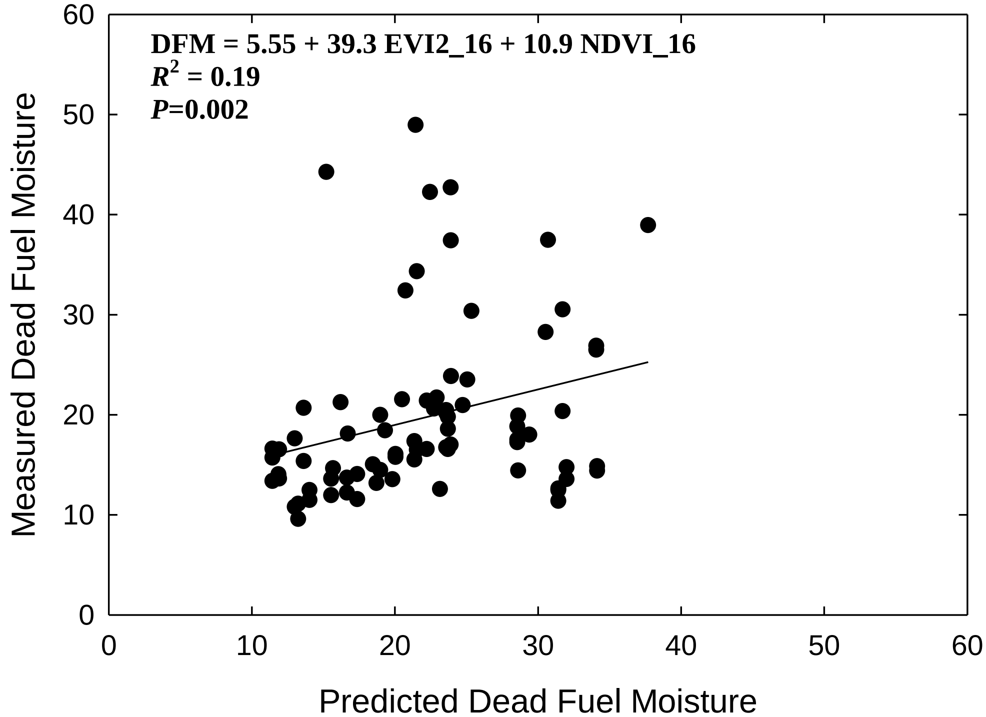

Figure 7: Dead fuel moisture prediction (x-axis) using MODIS vegetation indices vs. *in situ* live fuel moisture (y-axis) measurements.

CHAPTER 6. RESTORATION OF AN INVASIVE GRASS DOMINATED TROPICAL DRYLAND ECOSYSTEM: IMPACTS ON FUELS AND FUTURE FIRE POTENTIAL

Abstract

Ecological restoration is often challenged with simultaneously promoting native species recovery and managing for the synergistic impacts of disturbances such as fire and nonnative invasions. Hawaiian tropical dry lowland forest ecosystems are among the most endangered in the world, primarily due to land use change, invasive species, and increases in fire. The goal of this research was to investigate the potential for ecological restoration using native species to compete with the nonnative invasive grass *Megathyrsus maximus*, while also reducing future fire potential and behavior. *M. maximus* was suppressed with pre- and post-planting herbicide applications, and three suites of native species were outplanted in a randomized, complete block design that also included herbicide control and untreated control treatments. Species cover and fuels were measured 27 months after outplanting in each treatment plot, and potential fire behavior was modeled using the BehavePlus fire modeling software. Native outplant survival was moderate, averaging 51% across species. Compared to untreated controls, *M. maximus* cover was reduced by 76-91% in outplant treatments (P<0.001), and live and dead grass fuel loads were reduced by more than 92% (P<0.001) and 68% (P<0.05), respectively. Moisture content was much lower for native *Dodonaea viscosa* individuals (84%) than other native woody species (201-328%). However, neither fuel moisture nor modeled fire behavior (rate of spread, flame length, fireline intensity) differed between outplant, herbicide control, and untreated control plots. These results demonstrate that restoring a native species component to tropical dry forests is possible, but that ecological restoration will not necessarily alter the potential for fire and subsequent site degradation.

Introduction

A primary goal of ecosystem restoration is to return aspects of a natural ecosystem to treated areas (Hobbs and Norton, 1996), and to assist the recovery of an ecosystem that has been degraded, damaged, or destroyed (SERI, 2006). Disturbances, such as fire, are a critical component of all ecosystems, and play a large role in controlling species interactions and ecosystem structure and function (Turner, 2010). As such, ecological restoration typically involves promoting native species, but also necessitates managing for disturbance regimes that both promote native species and discourage non-target species (MacDougall and Turkington, 2005).

In many ecosystems, fuels management is a large component of ecological restoration, as fire regimes have been altered becuase vegetation communities are markedly different from their historical composition (Baker, 1994; Brooks et al., 2004). In temperate ponderosa pine ecosystems, for example, fire suppression has resulted in a large buildup of surface fuels, and prescribed fire and mechanical fuel treatments are often employed to return a mosaic of natural surface fire regimes to the landscape (Baker, 1994; Allen et al., 2002). The reduction in understory fuels can simultaneously restore ecological structure and function, and return fire intervals to their historic range of variability (Fule et al., 2001).

In tropical ecosystems, widespread nonnative invasive grasses often complicate ecological restoration efforts, as they often outcompete native species for limiting resources (Ammondt et al., 2012), and alter disturbance regimes. *Megathyrsus maximus,* [Jacq.] (guinea grass; previously *Panicum maximum* and *Urochloa maxima* [Jacq.]), an African pasture grass, has been introduced to many tropical countries as livestock forage (D'Antonio and Vitousek, 1992; Portela et al., 2009). It was introduced to Hawaii for cattle forage and became naturalized by 1871 (Motooka et al., 2003). Because *M. maximus* is well adapted to a broad range of conditions and can alter fire susceptibility by increasing fuel loads and fuel continuity (Chapter 3), it is one of the more problematic invaders in Hawaii and throughout the tropics. *M. maximus* recovers rapidly following fire by resprouting and seedling recruitment (Vitousek, 1992; Williams and Baruch, 2000), contributing to a positive feedback cycle between grass invasion and increased wildfire frequency and intensity (D'Antonio and Vitousek, 1992). Because guinea grass recovers quickly following fire and is competitively superior to most native species (Williams and Baruch, 2000; Ammondt and Litton, 2012), many areas in Hawaii are now faced with restoring woody communities to both facilitate native species establishment and manage for reduced fire occurrence and intensity.

Globally, tropical dry forests are among the most endangered ecosystems types (Vieira and Scariot, 2006) and in Hawaii it is estimated that less than 10% of this ecosystem type remains (Bruegmann, 1996). Remnant stands of Hawaiian dry forests often contain an invasive grass understory, making them susceptible to wildfire, further invasion and, ultimately, type conversion to nonnative grassland (Chapter 2). Fire is not believed to have historically played a large role in the evolution of Hawaiian tropical dry forest ecosystems due to lack of ignition sources and the absence of a continuous fine fuel bed (LaRosa et al., 2008). As a result, native Hawaiian species possess few adaptations to survive fire (Rowe, 1983; Vitousek, 1992) or to passively recover in the postfire environment (D'Antonio et al., 2011). As such, wildfire management is critical to the restoration of these ecosystems. Priority restoration objectives in these ecosystems typically include removal of the processes causing degradation (*i.e.*, anthropogenic wildfire, grass invasion, nonnative ungulates), and reintroduction of a native species component (Cordell et al., 2008).

The overarching objective of this research was to investigate the potential for using native woody species restoration outplantings to simultaneously compete with *M. maximus,* thereby reducing grass fuels and increasing native species cover, and reduce the potential for fire spread and intensity in these invasive grass-dominated ecosystems. Specific hypotheses included: (*i) M*. *maximus* cover and fine fuel loads would be lower in native outplant treatment plots than in herbicide control or untreated control plots due to competition between the grass and native plants (Ammondt and Litton, 2012); (*ii)* total fuel loads would be highest in untreated control plots due to chemical grass suppression in outplant and herbicide control treatments (Motooka et al., 2002); (*iii)* fine fuel moisture content would be higher in outplant treatments than in either herbicide control or untreated control plots due to shading by woody species (Bigelow and North, 2012); and (*iv*) outplanting native species would result in decreased potential fire spread and intensity compared to untreated control plots (Griscom and Ashton, 2011; Bigelow and North, 2012). These hypotheses were tested by quantifying species cover and fuels 27 months after outplanting and modeling fire behavior in a randomized complete block design (three native species outplant treatments, herbicide control and untreated control) in a lowland dry ecosystem dominated by *M*. *maximus* on the Island of Oahu.

Methods

Study site and restoration treatments

This study was conducted in the Waianae Kai Forest Reserve on leeward Oahu, Hawaii (300 m.a.s.l., 158°9'181"W, 21°28'53"N; Figure 1). Mean annual precipitation at the site is 1258 mm (Giambelluca et al., 2011), and mean annual temperature is 22°C (T. Giambelluca, Unpublished data). Soils are in the Ewa series (fine, kaolinitic, isohyperthermic Aridic Haplustolls) formed in alluvium weathered from basaltic rock (Soil Survey Staff, 2006). This study builds upon work describing initial survival and response of native species in the first 8 months after outplanting (Ammondt et al., 2012). In July 2009, the study area was mowed, on September 7, 2009 herbicide was applied to the entire study area except untreated control plots (see Ammondt, Litton et al 2012 for details), and in October 2009, a 0.13 ha fence was erected to exclude the feral ungulates (pigs, goats, cattle) that are common in the area.

Four blocks were established along an elevation gradient, and five 9 m^2 square treatment plots were set up in each block. On January 7, 2010, three different suites of native species were planted. All three outplant treatments included *Dodonaea viscosa* (L.) Jacq.) (a'ali'i), a shrub species, and *Plumbago zeylanica* L. (ilie'e), a ground cover and each contained one of three shade-producing canopy trees, either *Thespesia populnea* (L.) Sol.(milo), *Cordia subcordata* Lam. (kou), or *Myoporum sandwicense* (A. DC.) A. Gray (naio). Additionally, herbicide control (herbicide but no native outplants) and untreated control (no herbicide or native outplants) treatments were randomly assigned within each block. Outplants were obtained from a local native plant nursery (Hui Ku Maoli Ola, Kaneohe, Hawaii) in 10 cm containers. Twenty-five plants were hand-planted in each treatment plot (12 groundcover (*P. zeylanica*), 9 shrub (*D. viscosa*), and four canopy trees), and each plant was given 1 L of supplemental water immediately following planting and once per week for three weeks. Plants that died within one month of outplanting (21% mortality) were replaced. On April 12, 2010, November 30, 2010, and May 21, 2011, the pre-emergent, grass-specific herbicide fluazifop p-butyl (Fusilade® DX, EPA reg. no. 100-1070) was applied for continued suppression of *M. maximus* regrowth. In addition, herbaceous weeds were hand-pulled monthly from May-August, 2010 (Ammondt et al 2012).

Survival and Cover

Native species survival was measured on April 24, 2012, 27 months after outplanting. Percent cover of native species, *M.maximus,* and surface litter was measured on April 25-26, 2012 using a point-intercept method (81 point plot frame on each 9 m^2 treatment or untreated control plot).

Fuels

Surface litter and standing live and dead fine fuel loads (*M.maximus* and *P. zeylanica*) were measured in each 9 m^2 plot by collecting surface litter and clipping live and dead standing vegetation in four randomly located 625 cm^2 (25x25 cm) subplots and compositing by species. Within 5 hours of collection, samples were sorted into live and dead components, weighed, dried at 70° C for 48 hours, and reweighed to determine the mass of fuels per unit area and fuel moisture content relative to dry fuel mass.

Standing live fuel loads (i.e., live biomass) of *C. subcordata* and *D. viscosa* were estimated with species specific allometric models developed in Hawaii (Litton and Kauffman, 2008; Ammondt et al., 2012). *T. populnea* and *M. sandwicense* standing live fuels were quantified using new allometric equations developed in this study. Individuals of each woody species were planted around the perimeter of the study area, and destructive harvest occurred throughout the experiment to obtain individuals from a broad range of sizes. Plants were cut at the soil surface, separated into leafy and woody components, dried at 70°C to a constant mass, and weighed.

Live plant moisture content for native woody species was measured by clipping ≥ 3 leaves and ≥ 1 woody stem from 3 individuals of each species in each treatment plot (*D. viscosa, T. populnea, M. sandwicense,* and *C. subcordata*). Samples were immediately placed into plastic bags to retain moisture. Within 5 hours of collection, samples were sorted into herbaceous, woody, and seed components, weighed, dried at 70° C for 48 hours, and reweighed to determine moisture content of each plant component.

Fire Modeling

Potential fire behavior is commonly estimated using fire modeling software which either utilizes standard fuel models (Scott and Burgan, 2005) or custom, *in-situ* fuels and weather data as input parameters. Model outputs include potential for ignition, rate of fire spread, flame length, and fireline intensity (Andrews et al., 2005), allowing the user to estimate expected fire behavior for a given site. Inputs to the model can be altered to simulate fire behavior under different management scenarios (e.g., outplantings vs. controls). BehavePlus (version 5.0.5) fire modeling software was used for all fire behavior simulations.

All fuels data needed as input parameters in the BehavePlus 5.0 fire model were collected from each treatment plot, including live and dead fine fuels loads, live and dead fuel moisture, and fuel bed depth. Height of the tallest plant (grass or native) was measured in each subplot, and mean fuel height was recorded as 70% of the maximum fuel height (Burgan and Rothermel, 1984). Microclimate variables (air temperature, wind speed and direction) were obtained from an adjacent (~50 m) RAWS weather station. Live and dead fuel heat contents were measured by bomb calorimetry (Hazen Research, Inc., Golden, Colorado, USA). Previously published values for dead fuel moisture of extinction of *M. maximus* (Beavers, 2001) and woody surface area to volume ratio values for humid tropical grasslands (Scott and Burgan, 2005) were used. One-hour surface area to volume ratios were quantified using a LI-3100C portable leaf area meter (Li-Cor, Inc. Lincoln, Nebraska) and displacement in water. 20-ft wind speeds of 15 km hr^{-1} and 30 km hr^{-1} were used to simulate moderate and severe fire danger scenarios. A wind adjustment factor of 0.3 was used for all plots, to adjust the windspeed collected by the RAWS weather stations (20-ft wind speed) to that at the vegetation height (surface wind speed) (Andrews et al., 2005). Modeled fire behavior output consisted of probability of ignition (%), maximum rate of spread (ROS) (m/min), fireline intensity (kW m^{-1}), and flame length (m).

Statistical Analyses

Analysis of Variance (ANOVA) was used to elucidate differences in fuel loads (total, *M. maximus*, native plants), fuel moisture (*M. maximus*, native plant, scaled plot moisture), and predicted fire behavior (ROS, flame length, fireline intensity, probability of ignition). Block was treated as a random factor, and plot (treatment) was treated as a fixed factor. Tukey's multiple comparison tests were used following any significant ANOVA analysis to determine which treatment or control groups had significantly different means. For allometric modeling, predictive relationships between stem basal diameter and leaf, wood, and total standing fuels were developed using nonlinear regression methods. Power, quadratic, and cubic models were explored, and final model selection was based on R^2 values and residual plots. IBM SPSS v.20 (IBM SPSS, Inc., Chicago, IL) was used for all statistical analyses. Results were considered significant at $\alpha<0.05$ and marginally significant at $0.05 \leq \alpha \leq 0.10$.

Results

Survival and Cover

Survival of native plants averaged 51% across species, with 57% of *D. viscosa* (*n*=62), 56% of *T. populnea* (*n*=9), 38% of *M. sandwicense* (*n*=6), and 19% of *C. subcordata* (*n*=3) alive 27 months after planting. Survival was marginally higher for *D. viscosa* than *C. subcordata* (*P*=0.06), but no other differences in survival existed between species. Survival of *D. viscosa*, which was present in all outplant treatments, did not differ between outplant treatments (*P*=0.99). Individual *P. zeylanica* plants could no longer be distinguished to determine survival rates, but cover of this ground cover species was significantly higher in all outplant treatment plots than either herbicide control (*P*<0.001) or untreated control plots (*P*<0.001), as there was no natural recruitment of any native species in the herbicide or untreated controls. *P. zeylanica* ranged from 68-92% cover, and there was no difference between outplant treatments *(P*=0.25*).*

M. maximus cover was significantly reduced by outplant treatments, ranging from 9-24% cover in plots with native species outplants, and 91-100% cover in herbicide control and untreated control plots (*P*<0.001). There was no difference in *M. maximus* cover between outplant treatments (*P*≥0.44), or between herbicide control and untreated control treatments (*P*= 0.90). Litter cover ranged from 97-100%, and did not differ between treatments (*P*= 0.67).

Fuels

Basal diameter was a relatively accurate predictor of total standing fuel load for all native species ($R^2 \geq 0.61$), with the exception of *T. populnea* leaf fuel load ($R^2=0.38$) (Table 1), and all final models were highly significant ($P<0.01$). Log transformation of dependent and/or independent variables, inclusion of tree height, or inclusion of an additional term to account for the heteroskedasticity that is common in allometric models (Mascaro et al., 2011) did not significantly improve model fits. Mean individual plant standing live fuel loads across all treatments 27 months after outplanting was 738 g, 87 g, 335 g, and 30 g for *D. viscosa*, *T. populnea*, *M. sandwicense,* and *C. subcordata*, respectively. *D. viscosa* individual plant standing live fuel load was higher than *T. populnea* ($P=0.03$) but did not differ from that of *C. subcordata* ($P=0.30$) or *M. sandwicense* ($P=0.74$). There were no significant differences across the three canopy trees ($P=1.00$). When analyzed by treatment, *D. viscosa* standing live fuel loads did not differ with outplant treatment ($P=0.10$). When fuels for all woody native species were summed within each treatment plot, all outplant treatments were significantly higher than both the untreated control and herbicide control treatments ($P<0.01$), as there was no natural recruitment of native species. *M. sandwicense* outplant plots had more native woody fuels (6.47 Mg ha^{-1}) than *C. subcordata* treatments (3.27 Mg ha^{-1}; $P<0.05$), but neither of these treatments differed from *T. populnea* treatments (3.76 Mg ha^{-1}; $P>0.08$; Figure 2).

Fuel loads for the ground cover species *P. zeylanica* varied by treatment ($P<0.01$), with no individuals recruiting or growing into untreated control or herbicide control treatments. *C. subcordata* treatment plots had more *P. zeylanica* fuels (4.87 Mg ha^{-1}) than *T. populnea* (2.63 Mg ha^{-1}; $P<0.01$; Figure 2), and *M. sandwicense* treatments (3.68 Mg ha^{-1}) were marginally different in *P. zeylanica* fuels compared to other outplant treatments ($P>0.06$; Figure 2).

Native woody plant moisture content differed greatly by species (Figure 3). Mean *D. viscosa* moisture content was 84%, and was considerably lower than any other woody species ($P<0.01$). Mean *M. sandwicense* moisture content (328%) was higher than any other woody outplant species ($P<0.01$). Mean *T. populnea* (201%) and *C. subcordata* (203%) moisture content did not differ ($P= 0.99$). Mean moisture content of *P. zeylanica* (120-165%) did not differ between treatments ($P= 0.27$).

Live and dead *M. maximus* fuel loads were greatly reduced in all restoration treatments (Figure 2). Live grass fuel loads ranged from 0.55-0.68 Mg ha^{-1} in outplant plots, with no difference between outplant treatments (*P*=1.00 for all combinations). Herbicide plots averaged 3.34 Mg ha^{-1} of live grass fuels, and untreated controls averaged 8.13 Mg ha^{-1}. Untreated control plots had significantly more live grass than any outplant treatment (*P*<0.01) or herbicide control treatment (*P*=0.01). Standing dead *M. maximus* fuel loads were also highest in untreated control plots (*P*<0.05; 5.50 Mg ha^{-1}), with no significant differences between outplant treatment and herbicide control plots (0.22-1.76 Mg ha^{-1}; Figure 2). Litter ranged from 5.05-8.70 Mg ha^{-1}, and did not differ by treatment (*P*=0.15; Figure 2). Moisture content for *M. maximus* fuel loads ranged from 103-189% for live grass and 25-48% for dead grass and did not differ between treatments (live, *P*=0.36; dead, *P*=0.36). *M. maximus* live fuel moisture was on average 70% higher than *D. viscosa* moisture (*P*<0.001), and 176% lower than *M. sandwicense* moisture content (*P*<0.001), but no different than *T. populnea* (*P*= 0.09) or *C. subcordata* (*P*= 0.13)

There was a significant difference in total plot fuel loads (native plant + *M. maximus* fuels combined; *P*=0.03; Figure 2). Control plots had higher total fuel loads (22.33 Mg ha^{-1}) than all other treatments (*P*<0.05) except *M. sandwicense* plots (15.98 Mg ha^{-1}), where the difference was only marginally significant (*P*= 0.06). There were no differences in total plot fuel loads between outplant treatments (13.97-15.98 Mg ha^{-1}) and herbicide control plots (10.46 Mg ha^{-1}; *P*>0.05). When moisture content for the entire treatment plot was weighted by the biomass of each species present, mean live fuel moistures ranged from 118% to 182%, and mean dead fuel moisture ranged from 25% to 48%. However, there were no significant differences in live (*P*= 0.10) or dead (*P*= 0.41) moisture content between any treatment or control plots (Figure 4). Average fine fuel height ranged from 41.8 to 44.4 cm in herbicide control, *T. populnea,* and *M. sandwicense* treatment plots, which was significantly lower than average fuel height in untreated control plots (64.1 cm; *P*<0.05). Average fuel height in *C. subcordata* treatments (49.9 cm) did not differ from any other treatment (*P>*0.18 for all treatments).

Fire Modeling

Despite differences in fuels between treatments, no differences were observed in predicted fire behavior between untreated control, herbicide control, and outplant treatment plots ($P \geq 0.40$; Table 2). When surface windspeeds were simulated at 15 kph, rate of spread (ROS) was predicted to be 0.30-1.75 m min^{-1} (P= 0.40), flame length was 0.33-1.25 m (P= 0.48), fireline intensity was 36.5-759.8 kW m^{-1} (P= 0.71), and probability of ignition (POI) was 0.75-2.75% (P= 0.59). When surface windspeed simulations were increased to 30 kph, ROS was 0.53-3.48m min^{-1} (P= 0.40), flame length was 0.40-1.73 m (P= 0.45), fireline intensity was 64.5-1506.8 kW m^{-1} (P= 0.43), and probability of ignition (POI) was 0.75-2.75% (P= 0.59; Table 2).

Discussion

The results from this study, and others in Hawaiian dry lowland ecosystems that have been heavily invaded by nonnative grasses, suggest that ecological restoration of native species can be successful with substantial initial management that includes fencing, invasive grass control, and native species outplanting (Thaxton et al. 2012; Cabin et al., 2002b; Daehler and Goergen, 2005; Ammondt et al., 2012). Survival rates of native outplants at 27 months in this study were moderate (~51%), and when coupled with initial site preparation and chemical grass suppression, a significant reduction in *M. maximus* cover, fuel load, and fuel height was observed in outplant treatment plots. The herbicide control treatment (herbicide without native outplantings) resulted in significant decreases in fuel loads and fuel height as compared to untreated controls, but percent cover of invasive grass was not decreased by herbicide treatment alone, indicating that active outplanting of native species is necessary to effectively reduce fuel loads associated with this invasive grass.

When native woody species and invasive grass fuel components were considered together, there was more total burnable fuel in untreated control plots than most treatment plots. From a restoration perspective, rapid growth leading to increased biomass of native species and decreased invasive grass biomass and fuels would be considered a success (Ammondt et al., 2012). However, from a fuels and fire management perspective, the moisture content, continuity and arrangement of fine fuels must also be considered

(Pyne et al., 1996). At 27 months following outplanting, there was no vertical separation of surface and canopy fuels, so at this early stage of ecological restoration, native plants would likely contribute to, rather than hinder, surface fire spread. As the woody species grow into the canopy, one would expect lower surface wind speeds and a shading effect on the understory (Freifelder et al., 1998), resulting in separate surface and canopy fuel considerations for fire management (Scott and Reinhardt, 2001; Scott and Burgan, 2005).

Contrary to my original hypothesis, I did not see a difference in either live or dead fuel moisture between control and treatment plots. Canopy species (*T. populnea, M. sandwicense,* and *C. subcordata*) were much smaller by the end of the experiment than the intended midstory species (*D. viscosa*), so they did not provide the shading effect that was expected. Selection of appropriate species for outplanting is critical, and when objectives include both restoration and fire management, important trade-offs need to be considered. *D. viscosa* is a pantropical species, and is one of very few native Hawaiian plants shown to have fire adaptations (Hughes et al., 1991; Ainsworth and Kauffman, 2009). The rapid growth of this species in this study, and other restoration studies in Hawaii (Ammondt and Litton; D'Antonio et al., 1998; Medeiros and Von Allmen, 2006; Ammondt et al., 2012), and the broad range of habitats in which it is found make it an obvious choice for ecological restoration in Hawaii. The exceedingly low fuel moisture content of *D. viscosa* relative to the other native woody species and the invasive grass in this experiment, however, has important implications for fire spread and intensity, and is at least partially the reason why no differences were observed in modeled fire behavior across treatments. As a result, what has proven to be one of the best choices in a restoration setting for increasing native species cover in Hawaiian dryland ecosystems may not be a good choice where fire prevention is a priority, at least not during early stages of restoration.

While the restoration treatments clearly altered fuels, I saw no change in predicted fire behavior. There was a great deal of variability within and among treatments, but a trend toward decreased flame lengths, rates of spread, and fireline intensity in outplant treatments, particularly those that included *M. sandwicense*. As fuel moisture is a critical component in assessing the potential for fire (Pyne et al., 1996), I believe that the high density planting of low moisture *D. viscosa* had a large impact on modeled fire behavior.

As a hypothetical modeling exercise, I replaced the moisture content measured for *D. viscosa* with that measured for the canopy species in each plot and simulated fire behavior at moderate wind speeds, and fire behavior parameters decreased markedly in outplant treatments, with lower ROS and intensity than untreated control plots (P<0.05). While this *post hoc* fire simulation was not likely realistic in terms of predicting actual fire behavior in outplant treatments that were not included in the field experiment, I believe it demonstrates that an assessment of the moisture content of potential restoration species is an important avenue for further research when fire management is a priority consideration, as it often is in ecological restoration of dry ecosystems globally.

Probability of ignition, the likelihood that a firebrand will ignite fuels when landing on a fuelbed, was very low (<3%) for all treatments. This measure varies with dead fuel moisture, air temperature, and shading by canopy or cloud cover (Andrews et al., 2005). Dead fuel loads, which were primarily *M. maximus*, had fuel moistures ranging from 25-48% in this study, while previously reported dead fuel moisture for this species have been 10% or lower (Chapter 3). Fuel moisture of extinction for guinea grass has been reported at 40% (Beavers, 2001), meaning that fire will not carry through dead fuels with a moisture content over 40%. As some of the fuels measured in this study were above this threshold, and all were above the mean values reported for this species (Chapter 3), I would expect that these probabilities of ignition would change significantly if measurements were taken during a warmer, drier period when fires are more likely.

In conclusion, the synergistic impacts of altered fire regimes and nonnative grass invasion have been detrimental to the productivity and biodiversity of tropical ecosystems globally (D'Antonio and Vitousek, 1992; Williams and Baruch, 2000; Rossiter et al., 2003; Litton et al., 2006; D'Antonio et al., 2011). Restoration of these ecosystems and conservation of remnant intact ecosystem components often require active and adaptive management. Returning a native component to the landscape is possible, albeit management intensive, in Hawaiian dry ecosystems (Cabin et al., 2002a; Cabin et al., 2002b). A greater challenge, however, may be the alteration of the positive feedback between nonnative grass invasion and repeated wildfires (D'Antonio and Vitousek, 1992) to ensure that ecological restoration activities, as well as remnant native ecosystem components, are maintained in dry ecosystems throughout the tropics.

Table 1. Allometric models for predicting native species standing live fuels (i.e., leaf, wood and total biomass) from basal diameter in Hawaiian dry lowland ecosystems.

Dependent variable (*Y*)	N	a (SE)	b (SE)	R^2
Dodonaea viscosa				
Leaf fuels	20	0.08	2.25	0.78
Woody fuels	20	0.08	2.63	0.93
Total above ground	20	0.13	2.55	0.95
Thespesia populnea				
Leaf fuels	19	0.48	1.16	0.38
Woody fuels	19	0.01	3.05	0.73
Total above ground	19	0.14	1.97	0.74
Myoporum sandwicense				
Leaf fuels	22	0.39	2.08	0.90
Woody fuels	22	0.23	2.19	0.93
Total above ground	22	0.53	2.17	0.91
Cordia subcordata				
Leaf fuels	15	0.13	1.56	0.61
Woody fuels	15	0.15	1.50	0.66
Total above ground	15	0.28	1.54	0.71

*All models for *D. viscosa*, *T. populnea M. sandwicense* and *C. subcordata* are power functions ($Y = aX^b$) Y is the dependent variable (g dry weight), X is the predictor variable [basal diameter (mm)], and a and b are constants. *D. viscosa* equations are from Litton andKauffman (2008), and *C. subcordata* equations are from Ammondt *et al*.(2012)

Table 2. Predicted fire behavior under both moderate (15 kph) and severe (30 kph) wind conditions in outplant, herbicide control, and untreated control treatment plots in *M. maximus*-dominated, nonnative grass ecosystems on leeward Oahu, Hawaii. Means and standard errors are given for fire behavior parameters for each treatment (n=4).

Parameter	Wind condition	*Thespesia populnea**	*Myoporum sandwicense**	*Cordia subcordata**	Herbicide Control	Untreated Control	Model R^2	Block P	Treatment P
Rate of Spread (m min^{-1})	moderate	0.90 (0.3)	0.30 (0.1)	1.13 (0.7)	1.75 (0.3)	1.50 (0.7)	28.79	0.93	0.40
	severe	1.83 (0.5)	0.53 (0.2)	2.13 (1.58)	3.48 (0.6)	2.95 (1.4)	28.80	0.92	0.40
Flame Length (m)	moderate	0.78 (0.2)	0.33 (0.1)	0.75 (0.4)	1.15 (0.2)	1.25 (0.6)	24.64	0.98	0.48
	severe	1.10 (0.3)	0.40 0.2)	1.03 (0.6)	1.60 (0.3)	1.73 (0.8)	25.58	0.98	0.45
Fireline Intensity ($kW\ m^{-1}$)	moderate	200.50 (110.5)	36.50 (19.1)	316.00 (261.6)	413.25 (138.8)	759.75 (426.2)	27.83	0.5	0.71
	severe	416.5 (230.0)	64.50 (39.5)	611.50 (537.7)	828.00 (276.8)	1506.75 (845.0)	26.06	0.99	0.43
Probability of Ignition (%)	moderate	2.75 (1.8)	0.75 (0.8)	2.25 (1.0)	2.50 (0.9)	0.75 (0.8)	31.14	0.50	0.59
	severe	2.75 (1.8)	0.75 (0.8)	2.25 (1.0)	2.50 (0.9)	0.75 (0.8)	31.14	0.50	0.59

* *T. populnea*, *M. sandwicense*, and *C. subcordata* were planted as canopy species in three separate treatments. A consistent midstory of *Dodonaea viscosa* and a groundcover species, *Plumbago zeylanica* were planted in each outplant treatment plot.

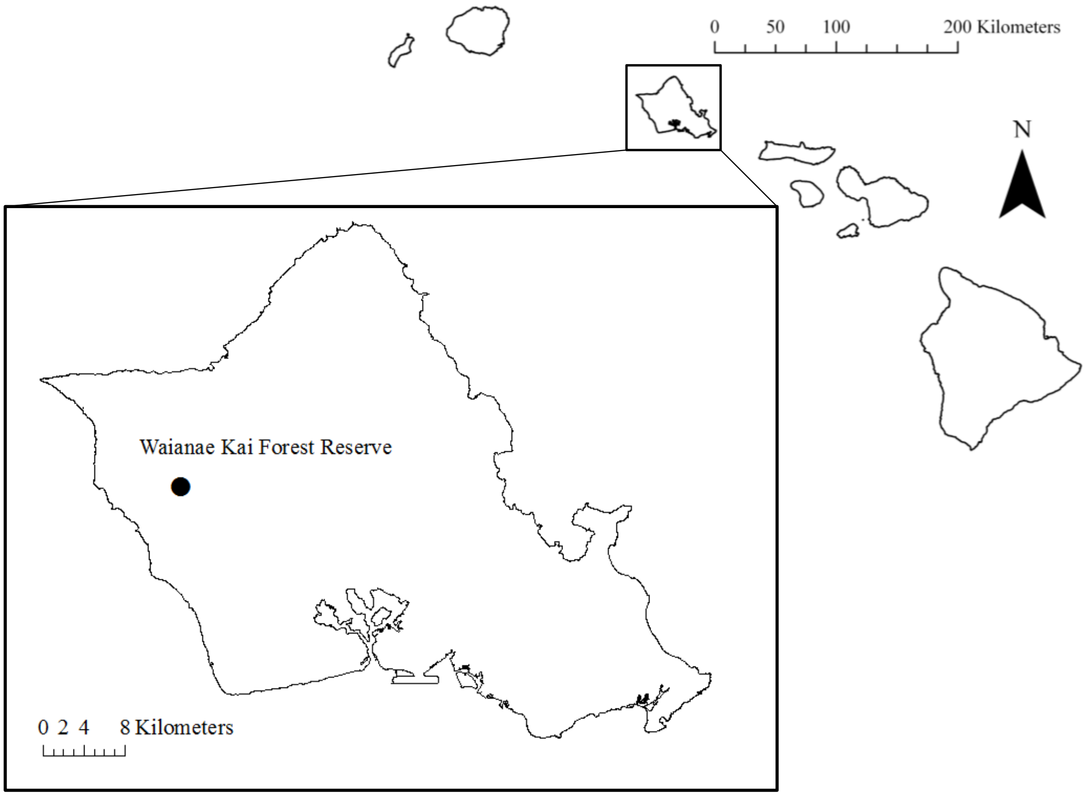

Figure 1. Restoration site in the Waianae Kai Forest Reserve on Oahu, Hawaii.

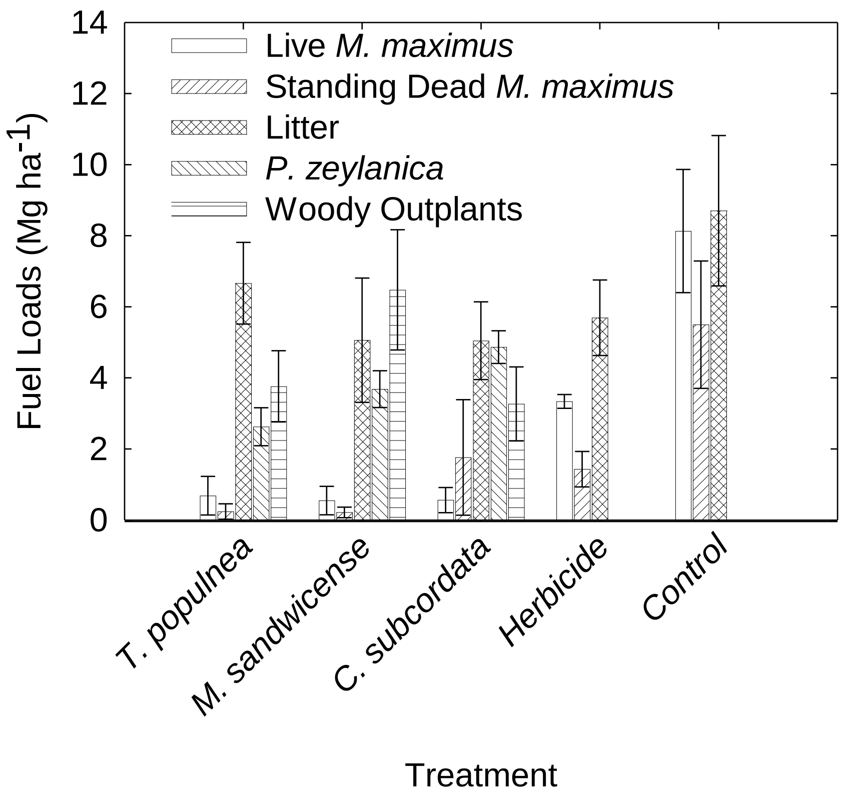

Figure 2. Fuel loads for all outplant, herbicide control, and untreated control treatments at Waianae Kai Forest Reserve, Oahu, Hawaii. Bars are means for each fuel component in each treatment, and error bars denote one standard error. Woody outplants (horizontal lines) consisted of both *D. viscosa* and one canopy species (either *T. populnea*, *M. sandwicense*, or *C. subcordata*). All ouplanted plots were also herbicided. Herbicide control plots and untreated control plots did not have a native species outplant component.

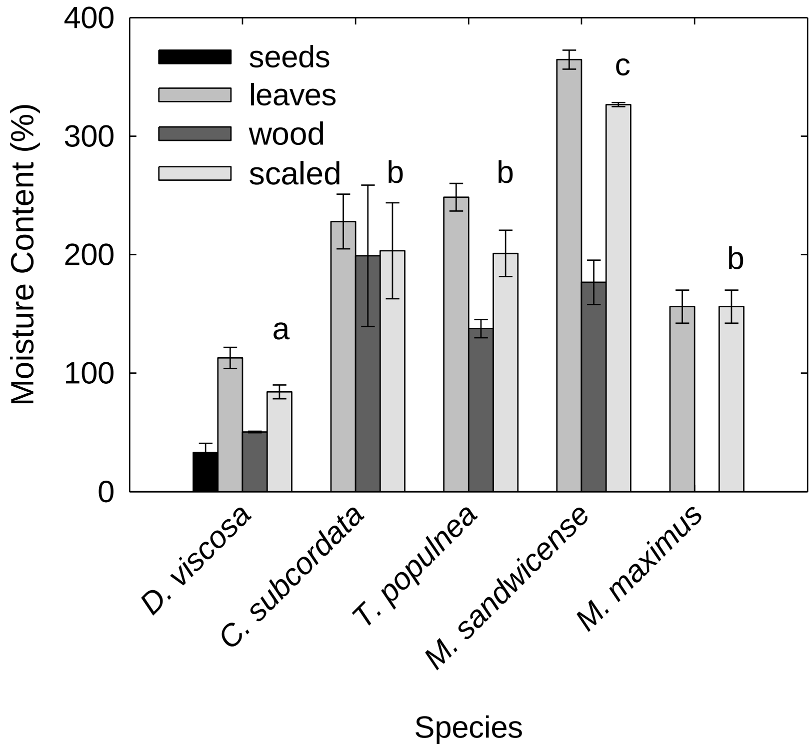

Figure 3. Native plant live fuel moisture content for *M. maximus* and restoration outplanting species used at Waianae Kai Forest Reserve. Moisture content for seed, leaves, and wood for each species are given, as well as overall moisture content for each species scaled by the proportional mass of each plant component. Lowercase letters denote significantly different scaled moisture content between groups at the $P<0.05$ level. Bars are means for each species and error bars are standard errors.

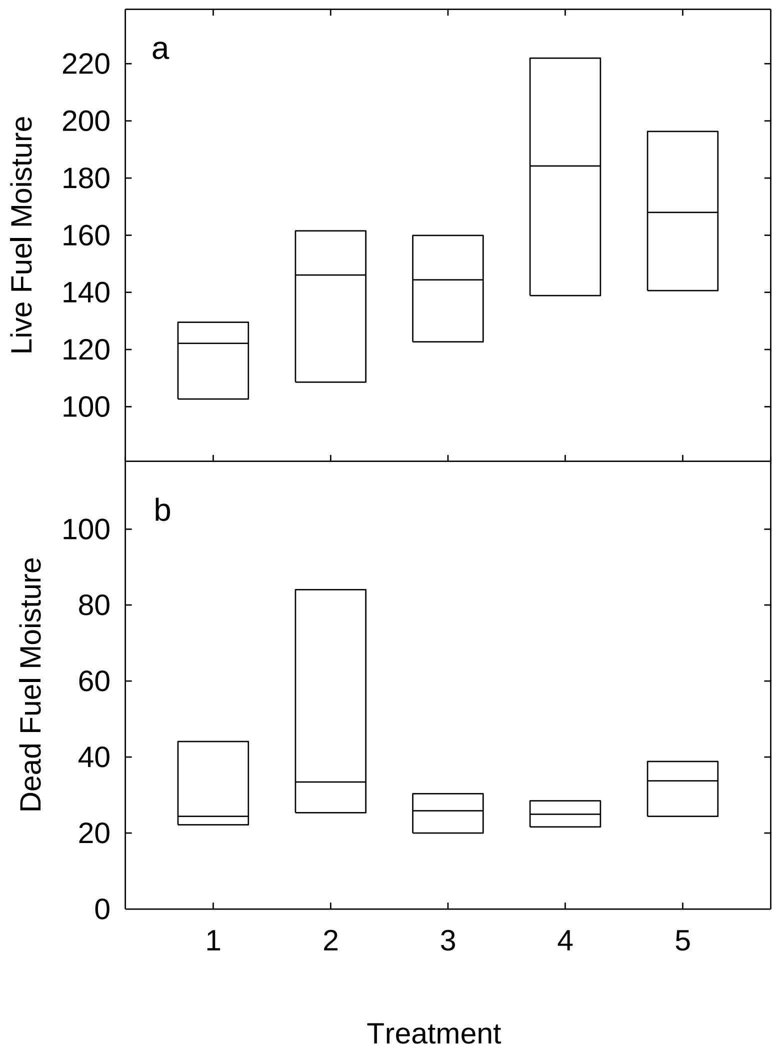

Figure 4. Plot level a) live and b) dead fuel moisture scaled by relative proportions of *M. maximus*, litter, and native outplant (*P. zeylanica, D. viscosa, T. populnea*, *M. sandwicense*, and *C. subcordata*) fuels. Restoration outplant treatments #1-3 contained *P. zeylanica*, *D. viscosa*, and either 1) *T. populnea*, 2) *M. sandwicense*, or 3) *C. subcordata*. 4) Herbicide only and 5) untreated control plots did not contain any native outplant species. No significant differences between treatments were found for either live or dead fuel moisture.

CHAPTER 7. CONCLUSIONS

The interactive influences of increased fire and nonnative grass invasion have altered many tropical ecosystems worldwide, often converting them to degraded grasslands with increased potential for more extreme fire behavior. The overarching goal of this research was to provide tools for improved wildfire prediction in guinea grasslands of Oahu, Hawaii using *in situ* fuels data collection, fire behavior modeling, remote sensing, and ecological restoration. Here, I summarize the major findings and management implications of this research, as well as suggest opportunities for future research needs.

In Hawaii, it is often assumed that wildfire removes the forest canopy and nonnative grasses subsequently invade and become dominant, resulting in a sequential conversion of forests to grasslands. This has been shown at the plot level in many ecosystems throughout the Hawaiian Islands (Hughes et al., 1991; Ainsworth and Kauffman, 2010), and in some cases, the invasive grass can persist for many years, and prevent native regeneration (D'Antonio et al., 2011). A large body of evidence has shown that the highly flammable African pasture grasses which have invaded many areas of the tropics are superior competitors (Williams and Baruch, 2000; Mack et al., 2001; Ammondt and Litton, 2012) that increase the potential for future fire (Brooks et al., 2004; Veldman and Putz, 2011).

When I tested plot-level findings on a landscape scale, in general the story was the same – with repeated fire, there is increased grass, and less forest – supporting the dominant paradigm. Also as expected, predicted fire behavior was more extreme in grasslands than in forests, with rates of spread 3-5x higher and flame lengths 2-3x higher in grasslands than in forests. In the grass-dominated, heavily utilized impact areas at both Schofield and Makua (inside the firebreak), this increased flammability coincided with increased grass cover and a concurrent reduction in woody cover over time. Many prescribed and accidental fires have occurred in both of these areas over the past 70 years (Beavers, *unpublished data*), and this area is maintained for active military training, so restoration of woody cover inside the firebreaks has not been a management priority. In the forested areas outside the firebreaks though, fire prevention is a priority, largely due to numerous threatened and endangered species in these forests (Beavers et al., 1999;

Beavers and Burgan, 2001). At Makua, where precipitation and fuel moisture are low (Chapter 3), fires are frequent, and response time from fire suppression crews housed at Schofield (60 km away) can be long, a similar pattern of increased grass cover through time has occurred. To address this, in 2004, military live fire training was eliminated from this installation. Despite these efforts, several large arson and roadside fires have occurred since. The other forested study area (Schofield Barracks) may be considered a bit more of a management success story. Here, I saw a very different trajectory, with more woody cover (albeit nonnative) currently than what was present 50+years ago. Schofield houses a well-trained fire management crew, who have made a reduction in area burned a high management priority in order to prevent further degradation of existing forests (Beavers and Burgan, 2001). Here I saw that an increased awareness of the need to aggressively manage fire and rapid response by well-trained fire personnel may help slow or even reverse widespread type conversion.

Tools to assist managers in predicting, controlling, and mitigating wildfire increasingly depend on modeling (*i.e.* fire prediction software, geospatial analyses, remote sensing) to simulate fire risk and behavior. However, to be accurate and realistic, models need to be based on field data and conditions. The field fuel data collection (Chapter 3) presented here represents the first wide-spread quantification of the spatial and temporal variability in guinea grass fuel loads in Hawaii. Overall, fine fuels and moistures exhibited tremendous variation, both spatially and temporally, highlighting the importance of real-time, site-specific data for the most accurate fire prevention and management.

Dead fuel loads were consistently high, making up at least half, and often closer to 75%, of the total fine fuel load in these grasslands. While live fuel moisture content is easier to estimate using remote tools (see Chapter 5) and is often referenced in regards to expected site flammability, the continuous standing dead and litter fuel loads provide year-round fire potential. The impact of these high dead fuel loads is evident in fire behavior predictions (Chapter 4). When fire simulations were run using the *in situ* custom fuel model, rates of spread and flame lengths remained moderate even at high fuel moistures, suggesting that this large dead fuel component would still drive fire behavior. In comparison, the national GR8 and GR9 humid tall grass models, which assume that ~85% of fuel loads are live, had minimal modeled fire behavior at high fuel moisture.

When the *in situ* fuels model was tested against data from actual prescribed fires, it did appear to perform better than prior models. However, all 5 of the validation fires occurred on the same day and in the same place, which greatly limits the range of fuel and weather conditions under which I was able to test these models. An important immediate research need is additional fire behavior data in guinea grass-dominated ecosystems across a wide range of fuel (moisture, fuel loads) and weather (windspeed, temperature) conditions. It is possible that multiple custom fuel models for guinea grass (e.g., high, moderate, and low loads) will be needed for precise fire behavior predictions in these grasslands, and validation fires for each model will be critical to assuring their applicability.

Fuel moisture content is an important driver of fire behavior (Andrews et al., 2005), yet it has been difficult to accurately estimate this parameter without *in situ* field data. Chapter 5 demonstrated that MODIS-based vegetation indices are better predictors of *in situ* live fuel moisture content (R^2=0.46) than currently used models based on RAWS data (R^2=0.37) for guinea grass ecosystems in Hawaii. Importantly, an added advantage of the MODIS-based prediction system is the continuous spatial coverage that satellite data provides. The topography of Hawaii is often quite steep, with rapid changes in important weather variables such as precipitation and relative humidity with spatial position (Giambelluca et al., 2011), making accurate moisture prediction using the RAWS-based system limited to small areas immediately adjacent to existing weather stations. While it is clear that there are significant advantages to using the MODIS-based prediction system, the RAWS-based tools are deeply ingrained in fire management circles, and it may be challenging to convince land managers that the remote sensing system is an improvement. An important next step will be to create a user-friendly interface for obtaining and processing the MODIS data and plugging it into a fuel moisture prediction algorithm, such that managers can quickly access this critical information for a given site.

Dead fuel moisture was poorly predicted by either MODIS (R^2= 0.19) or RAWS-based (R^2= 0.05) tools. Because dead fuel makes up such a large component of the total fuel load (see Chapter 3) and the moisture content greatly impacts fire behavior (Chapter 4), additional research on improved prediction of this fuel component is urgently needed.

Restoration trials were quite successful at reducing guinea grass fuel loads and returning a native species component back into these highly degraded systems (Chapter 6). While the first several months of this study required considerable management effort (herbiciding, outplanting, weeding, watering), beyond these initial efforts little was required to maintain these restoration plots. For restoration to be feasible at a management scale, it is imperative that native plants establish and survive without significant ongoing time and money expenditures. By the last year of this study, 27 months after outplanting, grass-specific herbicide was only applied once per year in the wet season. A valuable piece of information which I did not explore, but would greatly assist restoration planning would be a quantification of the costs associated with this restoration approach, including man hours, costs of native plants, herbicide, fencing, etc. An estimate of the cost per hectare of scaling a restoration project like this to a large management unit would help land managers assess feasibility of such a project.

Contrary to my hypotheses, modeled fire behavior was not decreased by any outplant treatment compared to untreated grass controls, despite greatly altered grass fuel loads. At 27 months following outplanting, there was no vertical separation of surface and canopy fuels, so native plants likely contributed to, rather than hindered, modeled surface fire spread. As the woody species grow into the canopy over time, one would expect lower surface wind speeds and a shading effect on the understory grass fuels (Freifelder et al., 1998). Continued monitoring of the fuel loads in control and treatment plots will elucidate long-term changes in fire potential as a result of restoration treatments. An important, but unexpected result of this research was the great differences in fuel moisture in the native plants selected for outplant treatments. *D. viscosa* had an average moisture content of only 84%, which was considerably lower than any other woody species. In contrast, average *M. sandwicense* moisture content (328%) was much higher than any other woody outplant species. These findings highlight the importance of careful species selection for any restoration project, and particularly for those in areas where fire management is a high priority. Additional research to determine the best native Hawaiian species for ecological restoration in the context of fire management is needed.

The research projects presented in this dissertation represent important steps in improved management of wildfire in guinea grass dominated ecosystems in Hawaii, and can inform similar work in grasslands throughout the tropics. Tools for improved wildfire prediction using *in situ* fuels data collection, fire behavior modeling, remote sensing, and field restoration techniques were explored, and many of the results suggest that, if implemented, there is capacity to better predict fuel characteristics and resultant fire behavior. Tall humid grasslands of African origin are now pantropical in distribution (Williams and Baruch, 2000), and many have very similar fuels characteristics to those presented here (Kauffman et al., 1998; Avalos et al., 2008; Portela et al., 2009), making these results relevant on a global scale. Improved fire prediction and management, coupled with ecological restoration, has the potential to increase biodiversity, reduce fire risk, and improve ecosystem structure and function in invasive grass dominated landscapes in Hawaii and throughout the tropics.

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