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Spatial and temporal variability of guinea grass (*Megathyrsus maximus*) fuel loads and moisture on Oahu, Hawaii

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Abstract. Frequent wildfires in tropical landscapes dominated by non-native 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. We 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, we sampled these four sites each summer for 3 years (2008–2010) and also sampled fuel loads, moistures and weather variables biweekly at three sites for 1 year. Live and dead fine fuel loads ranged spatially from 0.85 to 8.66 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, air temperature and precipitation. Overall, fine fuels and moistures exhibited tremendous variability, 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.

Additional keywords: fire behaviour, fire modelling, fuels modelling, invasive species.

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Introduction

The introduction and spread of invasive species is one of the leading causes of biodiversity loss in Hawaii (Loope 1998, 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 & S.W.L. Jacobs (Poaceae), previously *Panicum maximum* and *Urochloa maxima* [Jacq.]), a perennial bunchgrass 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 naturalised in the islands by 1871 (Motooka *et al.* 2003). Guinea grass quickly became one of the most problematic non-native 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 continuity. Year-round high fine fuel loads, particularly a dense layer of dead grass in the litter layer, maintain a significant fire risk throughout the year in guinea grass dominated ecosystems in the tropics. 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 (e.g. fire, land use change) and is competitively superior to native species under most environmental conditions (Ammondt and Litton 2012), many areas of Hawaii are now dominated by this non-native invasive grass (Beavers 2001).

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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). However, these prior studies 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} (Beavers *et al.* 1999; Beavers and Burgan 2001; Wright *et al.* 2002), but the driver of this variability is unknown. These overall values are generally similar to those reported for grass fuel loads in pastures elsewhere in the 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 2 years after the previous fire, demonstrating that the rapid accumulation of dead fuels may be the primary driver of fire spread and behaviour 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 a >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 loads and has been accurately predicted using climate variables (de Groot *et al.* 2005; Weise *et al.* 2005).

In Hawaii, research quantifying the spatial and temporal variability of fine fuels, ratio of live to dead fuels, fuel moisture content, and the relationship of these variables to current and antecedent weather conditions and time since fire are largely lacking and urgently needed. To accurately predict and manage fire occurrence and behaviour in areas dominated by guinea grass, it is imperative to first determine variability in fuels, particularly for dry areas of the island (Giambelluca *et al.* 2013) where anthropogenic fire ignitions are common and risk of fire is greatest. In addition, it is imperative to determine the drivers of this spatial and temporal variability in fuels 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 assess the spatial and temporal variability in guinea grass fuels (live and dead fuel loads and moistures) in 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, intra-annual and fine-scale (3 times per week)) in fuel loads and fuel moistures in guinea grass ecosystems in high fire risk areas and
(iii) relationship between antecedent 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.

Methods

Spatial and interannual temporal variability in guinea grass fuels

Research was initiated in the summer of 2008 to quantify the spatial and interannual variability of fuel loads in non-native dominated guinea grass ecosystems on Oahu's Waianae Coast and North Shore areas (Fig. 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 utilised by anthropogenic activity (i.e. military training, abandoned agricultural land) and are currently dominated by homogeneous stands of guinea grass with some invasive *Leucaena leucocephala* (Lam.) De wit (Fabaceae) in the overstorey. There is seasonal variability in precipitation patterns, with most precipitation falling in the winter months of November through April (Giambelluca *et al.* 2013). All study sites have deep, well drained soils that originated in alluvium or colluvium weathered from volcanic parent material (Table 1). Soils at Dillingham Airfield are 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), 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 overstorey 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 respectively due to cattle and military activity. 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 × 50-m sampling plot, three parallel 50-m transects were established 25 m apart and all herbaceous fuel was destructively harvested in six 25 × 50-cm subplots at regularly spaced fixed locations along each transect ($n = 18$ per 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 h of collection, dried in a forced air oven at 70°C to a constant mass and reweighed to determine dry mass and moisture content relative to oven-dried weight. Some live and dead woody fuels existed in our study sites, but we were primarily interested in

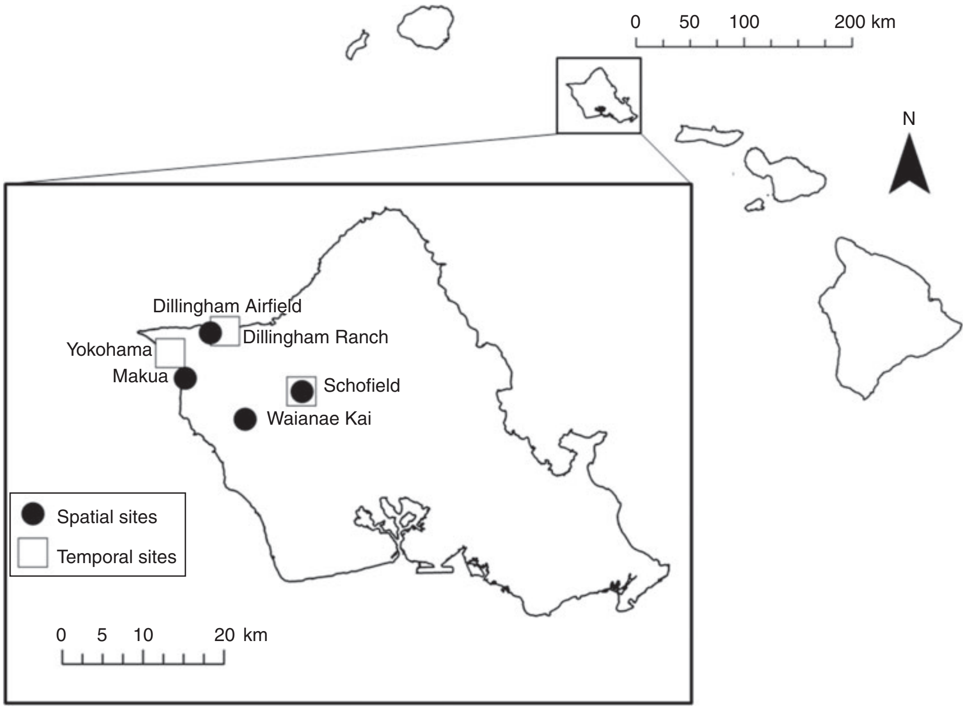

Fig. 1. Location of sample sites for spatial and temporal variability sampling in fuel loads across the Waianae Coast and North Shores of Oahu, Hawaii. Black circles indicate sites that were sampled during the summers of 2008, 2009 and 2010 (spatial and interannual temporal sites). White squares indicate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

Table 1. Descriptions of sites sampled for spatial variability in fuel loads and temporal variability in fuel loads and fuel moisture
MAP, mean annual precipitation (Giambelluca *et al.* 2013); MAT, mean annual temperature (T. Giambelluca, unpubl. data); Soil classifications were from the USDA Natural Resources Conservation Service (see http://websoilsurvey.nrcs.usda.gov/, accessed 30 May 2013)

Site	Elevation (m ASL)	MAP (mm)	MAT (°C)	Soil classification
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

characterising fine fuels associated with guinea grass, so did not include woody fuels in our 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%).

Intra-annual temporal variability in guinea grass fuels

Intra-annual variability of live and dead fuel loads and moisture content was measured approximately biweekly (27–33 sample dates per site) for 1 year (8 October 2009 through 24 September 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; Fig. 1; Table 1). All sites were dominated by guinea grass, with scattered *L. leucocephala* in the overstorey.

At each sampling location, one 50-m transect was established per sample date, along which all vegetation and litter in 25 × 50-cm subplots at six locations (0-, 10-, 20-, 30-, 40- and 50-m marks) was clipped and collected. Each subsequent transect was offset 1 m from and parallel to the previous sampling transect. Dillingham Ranch and Yokohama sites were flat and the Schofield Barracks site had a <5% slope, with a south-east aspect. Transects were oriented parallel to the slope (Schofield), or perpendicular to the road (Yokohama and Dillingham Ranch). 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, we 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 (autumn) rains (1 November 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, we used a repeated-measures mixed model analysis to determine whether differences exist in fine fuels that 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 $\alpha = 0.05$. Post-hoc multiple comparisons using the least square difference method were performed to elucidate differences between individual sites.

Analysis of intra-annual 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 that could be attributed to site or time sampled. Additionally, we were interested in potential relationships between fuel load and fuel moisture, and onsite weather variables (antecedent precipitation, maximum wind speed, 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 we were 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 that 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. Although 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) it is also useful to understand how longer scale (i.e. 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 strongest 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 strongest combinations of predictor variables to explain the change in live and dead fine fuel moisture at the finer temporal resolution (3 times per week for 4 weeks) were determined using backwards stepwise linear regression, with weather covariates derived from onsite RAWS as described above (Precip, Temp, RH). Additionally, 7-day average maximum sustained wind speed (Wind) was used as a covariate, after examining several date ranges. Because we wanted to see how antecedent weather altered fuel moisture between sampling dates, we 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 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. However, there was strong evidence that sites varied differently over time (site×year interaction; $P < 0.01$; Fig. 2). Makua and Schofield showed a trend of increasing fine fuel loads over time, whereas Waianae Kai had fairly constant fuel loads over time and Dillingham 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; Fig. 2).

Intra-annual temporal variability in guinea grass fuels

There was considerable temporal variability in biweekly total fine fuel loads at all three sites (intra-annual temporal sites, Fig. 1). Although 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 fall and winter (Fig. 3). Weather covariates and soil moisture were poor predictors of total fine fuel loads (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 (Fig. 3, Table 2).

Soil moisture (SM) ($P = 0.01$), 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 Temp (model estimate = 2.94) and RH (estimate = 1.91) increased live fine fuel loads, whereas increases in SM (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 Mg ha^{-1}).

Moisture content of fine fuels was variable over time, with large changes seen between sampling weeks (Figs 4, 5). Weather covariates and soil moisture were good predictors of the

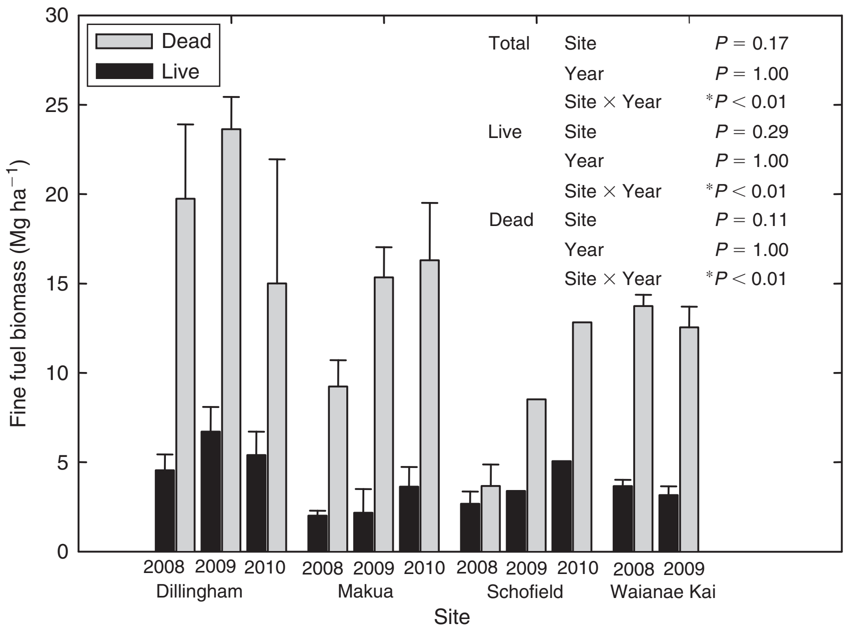

Fig. 2. Spatial variability in aboveground fine fuels in four guinea grass dominated sites along the Waianae Coast and North Shore areas of Oahu, Hawaii from 2008 to 2010. Bars are means for each site (Mg ha^{-1}) and error bars represent 1 s.e. Grey bars denote dead fine fuel loads and black bars live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

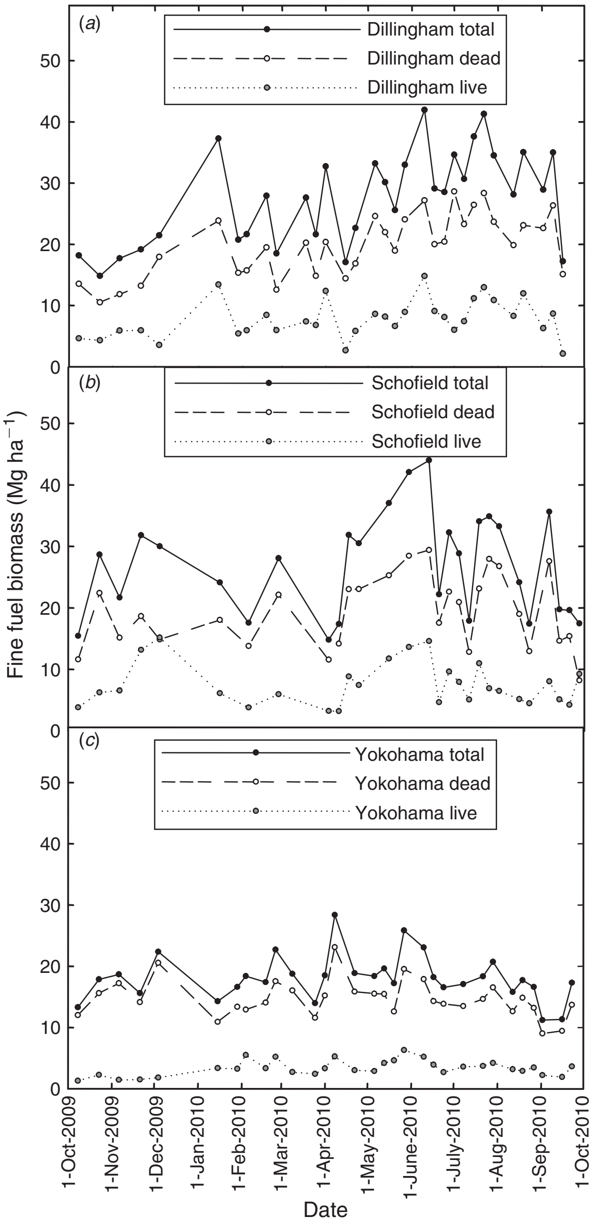

Fig. 3. Intra-annual temporal variability in aboveground fine fuels at three guinea grass dominated sites on Oahu, Hawaii from October 2009 to September 2010.

measured changes in live and dead fuel moistures over the year sampled. The best model for live fuel moisture (LFM) included SM (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 SM (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 (three sampling dates per week for 4 weeks), fuel moisture could not be accurately predicted using selected weather covariates. Although there appeared to be a trend of increasing fuel moisture following rainfall events (Fig. 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 RH 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 (ΔLFM = −382 − 4.35Wind + 9.20RH; $P = 0.11$) included only 7-day average maximum wind speed (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 (DFM) 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 (ΔDFM = −141 + 1.26 Temp + 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 behaviour across a landscape (Rothermel 1972; Pyne *et al.* 1996). Invasive grasses in the tropics alter fuel loads, typically by providing a continuous, highly flammable fuel source that can perpetuate 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.

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

Models were from the REML estimation method using SPSS:MIXED; Yokohama set as reference site. Variables in this table are: Temp, 7-day average maximum air temperature; RH, 7-day average minimum relative humidity; SM, soil moisture content; Precip, 7-day antecedent precipitation

Model Parameter	Estimate	SE	d.f.	*t*-statistic	*P*-value
Total fine fuel biomass (Mg ha^{-1})					
Intercept	18.65	1.85	16.17	10.09	0.000
Site					
Dillingham	9.68	2.60	15.83	3.72	0.002
Schofield	7.89	2.66	16.92	2.97	0.009
Yokohama	0.00[A]	0.00[A]	–	–	–
Live fine fuel biomass (Mg ha^{-1})					
Intercept	−84.02	28.75	38.62	−2.92	0.010
Site					
Dillingham	5.15	1.04	40.85	4.96	0.000
Schofield	3.07	0.86	26.93	3.56	0.001
Yokohama	0.00[A]	0.00[A]	.	.	.
Temp	2.94	0.96	36.82	3.06	0.004
RH	1.91	0.54	37.65	3.52	0.001
SM	−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					
Dillingham	4.37	1.86	14.37	2.35	0.034
Schofield	4.33	1.89	15.31	2.29	0.037
Yokohama	0.00[A]	0.00[A]	–	–	–
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
SM	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
SM	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]Yokohama set as reference site.

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 ranging 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).

Our results for Hawaii show even greater variability in guinea grass fuel loads, but generally support previously published estimates. Importantly, total fuel loads in mature guinea grass stands varied remarkably, both spatially and temporally, over a relatively small island landscape. Our data, like previous work, show some evidence for seasonal patterns in fuel loads (Table 2), but fluctuations over shorter time periods driven by weather better characterise 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 *v.* 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 fire risk 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 (Fig. 4),

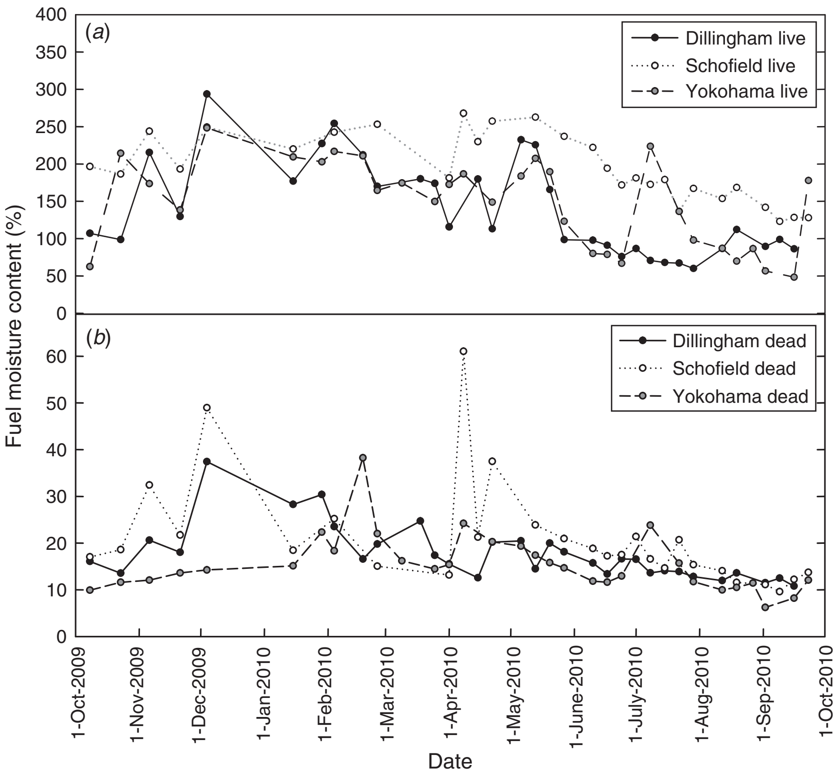

Fig. 4. Intra-annual temporal variability in (*a*) live and (*b*) dead fuel moistures at three guinea grass dominated sites from October 2009 to September 2010 (note: different scales on *y*-axis).

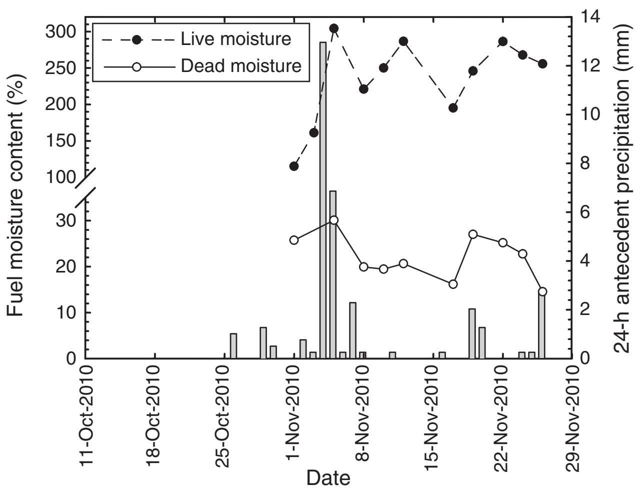

Fig. 5. Fine scale temporal variability in fine fuel moisture at Dillingham Ranch on Oahu, Hawaii over 4 weeks. Vertical bars denote rainfall events (mm; right *y*-axis) for the 3 weeks before and during sampling. Dates without bars had no precipitation. Dashed line with closed circles denotes live fuel moisture and solid line with open circles denotes dead fuel moisture.

indicating that these sites have adequate fuel accumulation and sufficiently low fuel moisture content to promote rapid fire spread most of the year, given an ignition source.

Live fuel moisture, which is affected by both biological processes and current and antecedent weather, also affects potential fire behaviour 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 intra-annual temporal models. Live and dead fuel moisture had strong relationships with weather covariates (Temp, RH, SM, Precip; Table 2). Fuel moisture is one of the most difficult parameters to predict, but one of the most important parameters driving fire occurrence and spread. Development of robust, site-specific predictive models for estimating fuel moisture, such as that provided here, should greatly advance capacity for modelling and managing fire in tropical landscapes.

Although our intra-annual models showed good predictive 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 on fuel moisture conditions. In our fine scale variability sampling, it appeared that periods of increased fuel moisture followed precipitation events (Fig. 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, wind speed 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 2000; Weise *et al.* 2005). These complex interactions may make prediction of live and dead fuel moisture difficult on these shorter time scales, but at longer temporal scales (intra-annual) these relationships were more robust.

This research provides an important first step in the management and prevention of fire in guinea grass dominated ecosystems in Hawaii by 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 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 modelling tools, such as fire behaviour and spatial models. Additional data 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.

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