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Research Article

Quantification of Surface Fuel Parameter in Selected Ecosystems in the Netherlands and England

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ABSTRACT

Estimation of biomass fuel loading is integral to reduce the impact or prevention of wildfires which pose a significant risk to both human lives and property. Predictive models for three major fuel categories (litter/duff, shrub and downed woody material) were developed for fuel parameters that contribute to surface fire behaviors in some of the more fire-prone areas on the Netherlands. Litter was defined as recently dead foliage and twigs on the ground, while duff is older, more decomposed material. Reduction of the number of potential parameters to measure should streamline the process of fuel load estimation. Certain parameters contributed more to predicting fuel loads than others in the litter/duff (O-horizon) and shrub categories, as the depth of the O-horizon and the O-horizon bulk density were the most significant variables, resulting in high (R^2=96) accuracy. For shrub dominated areas such as those where heather (*Calluna vulgaris*) is found, total height and basal diameter of the shrubs were the major contributing parameters, but the resulting model had a very low R^2, suggesting a need to revisit these communities and assess the potential fuels in another way, possibly by are, and not individual plant. Downed woody material differed between forest types. These results can assist land managers in this region in more accurate fuel estimation, therefore creating a more proactive approach to understanding and preventing the risks of wildfire events.

Keywords: Heather; Litter; Basal diameter; Downed woody material; Biomass

INTRODUCTION

Areas that were previously not considered to be fire-prone, such as the Netherlands and England, are experiencing a rise in wildfires, as changes in precipitation levels and heightened mean and seasonal temperatures have created a higher risk for fire danger [1]. In conjunction with a warmer, drier climate, there is the confounding factor of human activity and inhabitance. The Netherlands is one of the most densely populated countries in Europe, and combined with the small area of the country, results in a large percentage of land in the Wildland-Urban Interface (WUI), areas where wildland vegetation and buildings intermingle or meet. In the forested Veluwe region, where fire danger is generally higher than the rest of the country, most private property would be considered WUI [2]. This further complicates the wildfire issue challenges such as determining effective defensible space and coordinating fuel management on both sides of the interface. Educating citizens in both countries living in the WUI of the reasoning behind and importance of actions taken can aid with making effective management decisions. Research has been conducted on public wildfire preparedness and risk perception and canopy fuel estimations [2-4].

One potential effort to mitigate wildfire risk is the application of fuel reduction treatments, particularly in areas with high fuel loads. Although information on the application and efficacy of fuel treatments in the Netherlands and England is lacking, it is a common practice in many places around the world, including the western United States [5]. The main fuel reduction methods include both regular prescribed burning and mechanical treatments such as thinning of the understory and midstory forests strata. A regular prescribed fire interval approximating the historic fire regime of an area consisting of multiple burns over a period of time can reduce potential high-risk fire behavior. In the Netherlands this is problematic as they have no estimation of historic fire regimes or historical fire return intervals.

Vegetation structure and parameters play an important role in which variables can be used to predict biomass fuel loading. In shrub communities, foliar biomass, basal stem diameter and stem length have both been shown to be predictors of total fuels. Multiple models are most likely need to be estimated for communities dominated by grasses and shrubs due to the difference in influence of explanatory variables based on cover type [6-9]. Total biomass is a commonly used metric for representing total fuel load and is especially useful in shrub communities where heights are less than 2 m in height [10]. Biomass measurements

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can be estimated through dimensional analysis, or taking other measured parameters to predict biomass using regression equations [9]. Cover-based methods have also been shown to be effective in estimating above-ground biomass and are particularly effective in shrub and grassland ecosystems. Including height measurements in the predictive model can improve it and make predictions more accurate [11].

The goal of this project was to create predictive models to improve assessing wildfire hazard more efficiently, particularly in areas where fuel load measurement is time and labor intensive. Above ground biomass was used as a measurement of fuel loading and as the response variable in the models. The specific objectives of this study were to determine which surface fuel measurements contribute the most towards predicting biomass levels that might influence potential wildland fire behavior in fire-prone communities in the Netherlands and to develop models to estimate biomass fuel loading.

MATERIALS AND METHODS

Site description

From 2012-2017, surface vegetation data was collected in various ecosystems in the Netherlands and England, utilizing methodologies from North America [6,12]. Emphasizing surface vegetation considers the ladder fuel effect, in which surface fires can result in more severe fires if they spread to canopy vegetation [13]. While most of the sites were in the Netherlands, sites in England were utilized to allow measurements in ecosystems deemed too fragile in the Netherlands to enter. Many of the study areas are described in the BIJ12 Nature Information and Management Unit in the Nature and Landscape Index [14].

Pine, oak and beech forests often contained Scots pine (*Pinus sylvestris*), black pine (*Pinus nigra*), pedunculate oak (*Quercus robur*) and beech (*Fagus* spp.). Scots pine is the most common pine species in the Netherlands, while black pine often dominates along the coast. Silver birch (Betula pendula) can also make up a portion of the over and mid-stories. Shrub species include blackberry (*Rubus* spp.), holly (*Ilex* spp.), mountain-ash (*Sorbus aucuparia*) and sea buckthorn (*Hippophae rhamnoides*). Naturalized Douglas-fir (*Pseudotsuga menziesii*) often grows alongside shade-intolerant trees such as larch (*Larix* spp.) and birch (*Betula* spp.) until it becomes dominant and shades out those species. It also grows with European blueberry (*Vaccinium myrtillus*), bunch grasses and rushes (*Juncus* spp.) in the understory [15,16].

Grassland types are influenced by differences in site moisture and soil nutrient availability, as well as past and current management practices. Wet grasslands are regularly flooded by nearby bodies of water and many sedge species (*Carex* spp.) occur in this cover type. Heather occurs frequently and when in large numbers are referred to as heather grasslands [14].

Heather-dominated landscapes occur on both dry sites and wet peat bogs. Dry sites mainly consist of heather, but can also support perennial grass species and juniper (*Juniperis* spp.) thickets. Mosses and forbs form the groundcover layer, often on low nutrient soils [17]. On wet heather sites, other vegetation includes blackberry and Scotch broom (*Cytisus scoparius*) thickets, grasses such as wavy hair grass (*Deschampsia flexuosa*) and purple moor grass (*Molinia caerulea*), *Sphagnum* moss, and some Scots pine or downy birch (*Betula pubescens*) [14].

Dune grasslands are composed of species such as marram grass (*Ammophila arenaria*), wavy hair grass, and grey hair grass (*Corynephorus canescens*). Dune valleys are moist areas between dunes, with shrub species such as creeping willow (*Salix repens*) and blackberry thickets on edges of the valleys. Wet dune heather has a mossy ground layer and contain species such as crowberry (*Empetrum nigrum*) and creeping willow, while drier sites contain heather and sand sedge (*Carex arenaria*). Dune forests have Scots pine, pedunculate oak, silver birch, and beech. Understory species include hawthorn (*Crataegus* spp.), buckthorn, and common elderberry (*Sambucus nigra*), and dewberry (*Rubus* spp.) [14].

Peat systems in the Netherlands can be categorized as high peat or low peat. High peat systems are located in the northern, central and southern sandy regions of the country, while low peat systems exist in the northern and western coastal plain regions [18]. *Sphagnum* mosses can cover large areas of the ground, and in wetter sections heather and reed (*Phragmites* spp.) are present. In drier sections sedges and thickets of blackberry and Scotch broom can be observed. In low peat communities, *sphagnum* mosses comprise the main ground cover. Heather-dominated swamp areas can be present in some areas with swamp sawgrass (*Cladium mariscus*), rushes and reeds present in areas not covered in water [14]. Peat forests can occur in both high and low peat systems, with *Sphagnum* moss, small shrubs and downy birch. Thickets formed by gray willow (*Salix cinerea*) and black chokeberry (*Aronia melanocarpa*) are common [14].

Site locations

The 2012 study areas were near Hoenderloo and Assel in the Netherlands, with beech, Douglas fir, grassland, heather and Scots pine overstories sohwn in Figure 1 [19]. There were two grassland plots and five Douglas-fir plots with understory species including European blueberry, bedstraw (Galium spp.), ferns, bunchgrass and wavy hair grass (*Deschampsia flexuosa*). Scots pine seedlings were also represented in the understory and mountain-ash the mid and overstory of some plots. Heather plots were either almost pure stands of heather or mixed communities also containing grass or scattered Scots pine. Scots pine areas supported an understory of bunchgrasses, wavy hair grass, blueberry, rushes, as well as birch and oak seedlings and in the midstory of some plots, mountain-ash was present.

In 2013, study areas were in dune sites on Texel Island and near Haarlem, with marram grass and grey hair grass dominant, in addition to various sedge species shown in Figure 1. Shrub species such as rose (*Rosa* spp.), heather and blackberry were also present, along with mosses and forbs. Thickets of creeping willow and blackberry were noted as well. Fire behavior in these plots was rated as very high to extreme [20].

Sites were established in 2014 in the Northumberland National Park in the United Kingdom in various peat ecosystems: Although these sites were in the U.K., they were chosen since they did represent systems that are present throughout Europe, including in the Netherlands shown in Figure 2 [21]. Plots consisted of vegetation common to peat systems, with purple moor grass, wavy hair grass and common rush (*Juncus effusus*) present, in addition to a layer of *sphagnum* moss; heather and hare's-tail cottongrass (*Eriophorum vaginatum*) was also present in some of the plots, some plots had overstories dominated by black alder and goat willow (*Salix caprea*), with downy birch present in shrub form.

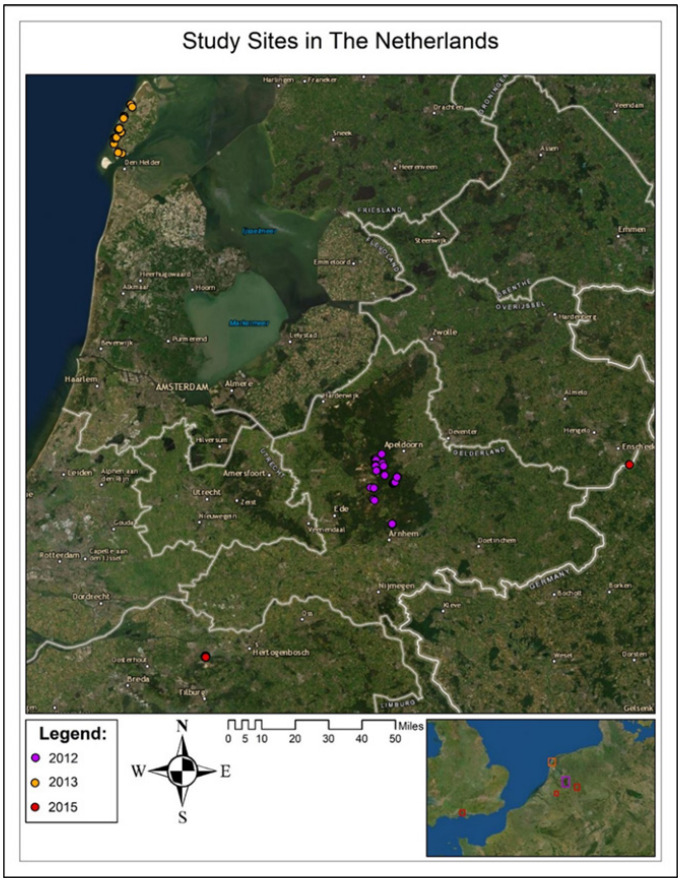

Figure 1: Study sites in the Netherlands.

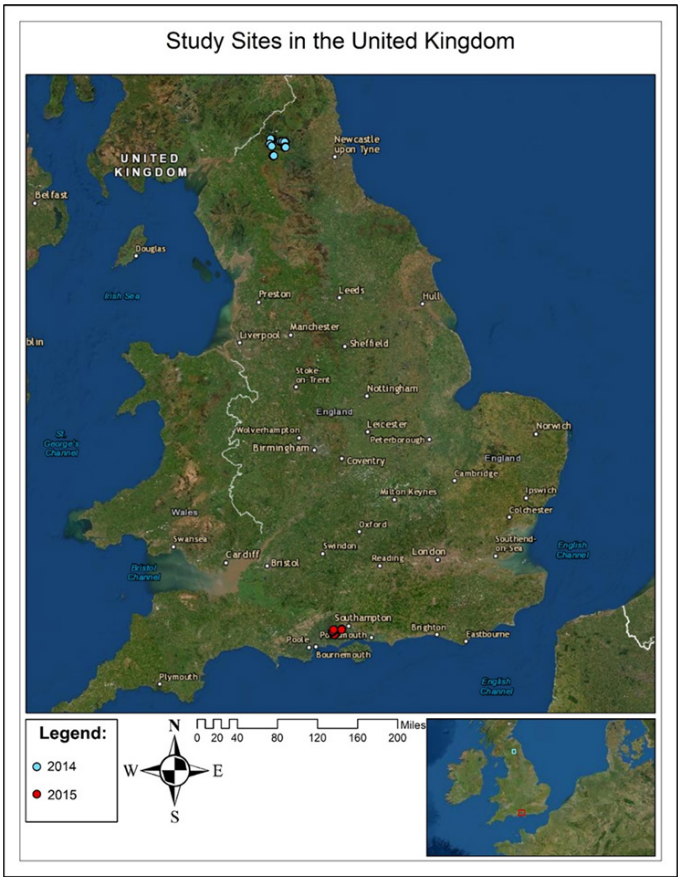

Figure 2: Study sites in the United Kingdom.

In 2015 study sites were in both the Netherlands and the U.K. shown in Figures 1 and 2. Plots in the Netherlands were in dunes and peats areas in the province of North Brabant. In the U.K., plots were in the New Forest National Park in a mixed forest cover type. The mixed forest plots in the U.K. had an overstory of Scots pine, Norway spruce (*Picea abies*), beech, pedunculate oak and silver birch. The understory was bracken, holly, heather, common rush and moss [22].

Field methods and data collection

Plot layout from 2012 through 2015 followed an adapted plot design shown in Figure 3 [12]. Two layers of the O-horizon, litter (recently dead foliage and twigs on the ground) and duff (older, more decomposed material) depths were measured in all subplots. A densiometer was used to determine the percentage of open overstory canopy and each overstory species' Diameter at Breast Height (DBH), total height, and basal diameter measured. Canopy diameters were measured at both the widest point and then at 90 degrees. For shrub and understory measurements, the species were recorded. Understory vegetation was categorized into seedlings and saplings, while shrub density, number of stems and basal diameter were recorded and two canopy diameters were taken for each shrub.

Measurements used to determine fuel loads were taken along the transects in the sample area. Line intercept percentages of species and ground cover were taken at each of the 25 plots as well as the six mid/overstory subplots not placed on an arc. Litter and duff bulk densities were measured by filling a can of a known volume with litter or duff, then drying and weighing it.

Data analysis

Data were categorized as either herbaceous, litter/duff, shrub and downed woody material and linear regression analysis performed for each to demonstrate the relationship and predictive capability between the variables in each fuel category to biomass (Table 1). Data were analyzed using RStudio 4.2.0 [23].

Using litter depth, duff depth and bulk density to predict loading in terms of available biomass, mean values were calculated for each variable for each plot, with plots placed in one of five cover types, resulting in 26 total mean values for each litter/duff parameter. Summary statistics were calculated for each variable using the psych package and the describe function [24]. Assumptions of linearity, independence of observations and normality were tested in the base R package. Linearity was tested by using the plot function to demonstrate the relationship between each vegetation parameter and biomass. Due to the nonlinear relationship between litter depth and biomass, litter depths and duff depths were combined into total O horizon depth. Independence of observations was tested by using the cor function in the R base package to check for potential correlation between variables. Normality of distribution of the data was tested using the hist function to graph the variables in a histogram.

To determine differences among and between cover types, a Kruskal-Wallis test and a pairwise comparison using the Wilcoxon rank sum test were performed using the stats package [23]. A nonparametric test was utilized because of the non-normal distribution of the data. A boxplot was produced to demonstrate the distribution of data in the five cover types. The Akaike Information Criterion (AIC) was applied using the AICcmodavg package to discern the best variable selection among a set of possible models [25]. This method is preferable to traditional model selection approaches such as forward, backward and stepwise selection because it offers more consistent and robust estimates and does not rely on significance values to show best fit. Following model selection, MLR was performed using the linear model function to fit the data to a linear model.

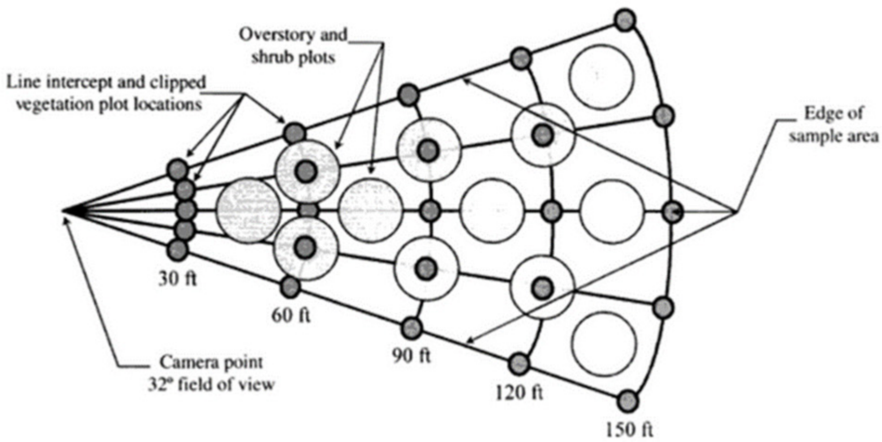

Figure 3: Original plot layout design by Ottmar et al., adapted for use in field measurements. Units are English, not metric, following the original layout first used in the U.S. 30 ft=9.14 m; 60 ft=18.29 m; 90 ft=27.43 m; 120 ft=36.58 m; 150 ft=45.72 m.

Table 1: Initial explanatory variables by growth form and year selected, split into the three fuel categories based on relevance.

Year	Shrubs	Grasses	Litter
2012	Basal diameter (cm), Density (%), Height (cm)	Wet/dry weights (g)	Litter/duff depths (cm), Bulk density (g/cm^3)
2013	Basal diameter (cm), Density (%), Height (m)	Herbaceous density (%)	Litter/duff depths (cm),
2014	Basal diameter (cm), Height (m)	Herbaceous density (%)	Litter/duff depths (cm)
2015	Basal diameter (cm), Height (m)	-	Litter/duff depths (cm), Bulk density (g/cm^3)

A similar methodology was used to analyze the shrub fuel load data. The variables stem count, basal diameter (cm), total height (cm), and canopy diameters 1 and 2 (cm) were all tested to determine their ability to predict fuel loading, represented using dry weight (g) of biomass. Variables were first standardized, as the original data collection was not performed using consistent units. The dominant species in each plot was specified, and the dry weight was calculated. The summary statistics and assumptions of linearity, independence of observations, and normality were obtained and tested using the same methods as the litter/duff fuel category. A Kruskal-Wallis test to test for significant differences between shrub species was done.

To perform regression analysis, the dataset was further split into five significant cover types. Using a minimum sample size requirement recommended for regression analysis ($n \geq 30$), the dataset was narrowed down to five cover types: Heather, Scots pine, dune heather, dune valley and peat heather [26]. For each type, a separate analysis was followed to produce five different regression models. First, simple linear regression was applied to each of the five variables to determine the nature of the relationship between these and dry vegetation weight. Then a separate AIC was run for each of these significant cover types to find the best fitting regression model. The assumptions for regression were tested for each model produced by creating a histogram to check for normality and by looking at the Pearson's correlation coefficients between variables.

For the Downed Woody Material (DWM) data, a MLR analysis was not performed due to the type of variables collected. DWM was measured using the planar intercept method [22]. Following this method, DWM was divided into 1 h, 10 h, 100 h, 1000 h solid, and 1000 h rotten timelag values amongst 17 cover types. These categorical values could not be utilized in a predictive model. Metric tons per hectare of downed woody material were used as a measurement of available biomass. Summary statistics and assumptions of linearity, independence of observations, and normality were obtained following the same methods as the previous fuel categories. The data were not found to follow normal distribution, so a Kruskal-Wallis test was performed to determine differences in tons per acre among cover types. The cover types were then divided into three subcategories: Forested, peat and dune types. Each of these subcategories were tested for differences amongst them again using the Kruskal-Wallis test. A post-hoc Wilcoxon rank sum test was used to determine which cover types in the forested and peat subcategories had significant differences. A boxplot was made for all three subcategories to demonstrate the distribution of data of each cover type.

RESULTS

Litter and duff had significant differences in total biomass among and between the five cover types (p-value=0.001); differences were greatest between forested and non-forested cover types, with litter/duff biomass levels at or nearly 0 in grassland and heather covers. AIC analysis indicated that the best model selection included total O-horizon depths and bulk density (Table 2). Significant relationships were found between these vegetation parameters and biomass fuel loading. The model with separate litter and duff depths was not as strong, indicating that combination of these two variables can occur with no adverse effect on total biomass prediction. Significant positive relationships exist between total fuel loads demonstrated through biomass and total O-horizon depth and bulk density ($p<0.0001$ and $p<0.001$, respectively), as total O-horizon depth and bulk density increase, total biomass increases as well. Multiple linear regression with the best model equation had an R2 value of 0.967 (Table 3).

Significant differences between the amounts of dry vegetation weights existed between species (p-value<0.001); while all species showed similar ranges, *vaccinium* had higher dry weights than the others, most likely due to high stem counts. Since heather is a species of interest, as its volatile compounds have the capacity to significantly influence fire behavior differences.

Shrub stem count caused the models to have an inflated R^2 value, so it was removed from the analyses. AIC results indicated that for each cover type, the most significant variables were total height and basal diameter (Table 4). The models for the heather (R^2=0.13) and Scots pine (R^2=0.20) cover types contained only total height, while the dune heather cover type (R^2=0.07) contained only basal diameter, and both dune valley (R^2=0.20) and peat heather (R^2=0.62) cover types contained total height and basal diameter (Table 5). The predictive power of these models is obviously relatively weak; however, both total height and basal diameter were significant in estimating shrub fuel loading in these cover types. The measurements of canopy diameter were not included in any of the best-fitting models, but future analysis might consider them, as they can serve as a surrogate for shrub density (Table 6).

Table 2: Akaike information criterion for the litter and duff fuel category showing the best fit model with the potential explanatory variables of litter, duff, combined total O-horizon and bulk density.

Proposed model	K	AICc	Delta AICc	AICc weight	Cumulative wt	Log likelihood
Total O-horizon+Bulk density	4	573.93	0	0.73	0.73	-282.01
Litter+duff+bulk density	5	575.99	2.06	0.26	0.99	-281.49
Total O-horizon	3	582.2	8.27	0.01	1	-287.55
Bulk density	3	628.27	54.34	0	1	-310.59

Table 3: Parameter estimates for the predictive model used to estimate above ground litter and duff biomass (R^2=0.97).

Variables	Estimate	Standard error	T-value	Pr (>|t|)
Intercept	-5867.7	4874.9	-1.2	0.241
Total O-horizon	39269.6	2893.3	13.57	<0.0001
Bulk density	2453.5	701.8	3.5	0.0019

Table 4: The best fitting models for predicting fuel loading the for five shrub cover types.

Cover type	Model	K	AICc	AICc weight	Log likelihood
Heather	total height	3	592.01	0.37	-292.76
Scots pine	total height	3	526.64	0.34	-260.07
Dune heather	basal diameter	3	553.65	0.29	-273.6
Dune valley	basal diameter+total height	4	330.63	0.43	-160.65
Peat heather	basal diameter+total height	4	454.04	0.56	-222.71

Table 5: Parameter estimates for each of the predictive models used to estimate above ground biomass (dry weight in grams) for the five shrub cover types.

Variables	Estimate	Standard error	T-value	Pr (>|t|)
		Heather		
Intercept	370.75	30.4	12.2	<0.0001
Total height	-2.08	0.71	-2.95	0.0048
		Scots pine		
Intercept	226.77	13.77	16.47	<0.0001
Total height	1.66	0.44	3.74	0.0005
		Dune heather		
Intercept	247.82	11.01	22.51	<0.0001
Basal diameter	4.84	2.15	2.26	0.028
		Dune valley		
Intercept	253.24	8.17	30.98	<0.0001
Basal diameter	5.82	1.95	2.98	0.0054
Total height	-0.52	0.17	-3.07	0.0043
		Peat heather		
Intercept	167.71	4.48	37.43	<0.0001
Basal diameter	6.96	0.74	9.41	<0.0001
Total height	0.38	0.09	4.5	<0.0001

Table 6: Biomass means, standard deviations and ranges of each category for each of the fuel categories.

	Mean	Standard deviation	Range
		Litter/Duff	
All	96775	73193.48	0.00-200114.00
		Shrub	
Dune heather	271.3	28.52	202.50-321.80
Dune valley	237.4	27.89	195.60-302.90
Peat heather	210.7	9.64	191.30-236.50
Heather	284.1	59.68	198.80-390.00
Scots pine	274.6	41.07	201.20-338.30

All	257.2	49.74	191.30-428.70
Downed woody material			
Forested	1143.5	1327.43	0.00-5024.00
Dune	117.05	218.39	0.00-888.21
Peat	142.69	452.66	0.00-2067.10
All	498.47	992.36	0.00-5024.00

Significant biomass differences between cover types were not detected following the initial Kruskal-Wallis test (p-value>0.05), so the subcategories were then tested using the same method, and significant differences within forested cover types and peat cover types were apparent (p-value of 0.002 and 0.0003, respectively). No significant differences were observed between the dune cover types. Of the forested cover types, dune forest and Douglas-fir communities displayed the greatest differences (p-value=0.024), differences are also shown between Douglas-fir and new forest plots (p-value=0.041).

Of the peat cover types, differences between peat bog and peat forest plots were the most significant (p-value=0.035). Peat forest cover types significantly differed with the peat heather cover type (p-value=0.056 in 2014 and p-value=0.081 in 2015). Interestingly, the peat heather and heather cover types differed significantly from each other (p-value=0.084).

DISCUSSION

Several factors including fuel category and predominant vegetation structure and composition influenced which variables were more useful in predicting total above ground biomass. For the shrub fuels category, cover types were too varied in vegetation species and composition to develop one singular comprehensive predictive model for total dry weight of fuels, so five separate regression models were developed for the cover types. In each of these models, total height, basal diameter, or a combination of both were found to be the most significant variables. In the Downed Woody Material (DWM) fuels category, significant differences in fuel loading were present amongst cover types

The measurement of fuels can be difficult even when utilizing standardized and established methodologies. Fuels are complex in structure and highly variable across large spatial scales. Because of this complexity, ideally all vegetative components of wildland fire fuels would be measured separately. Litter and duff have differing effects on fire behavior and often burn independently of each other, particularly in regions where duff buildup is high due to longer fire return intervals [27]. The duff layer typically smolders and therefore results in higher, more prolonged temperatures around the base of trees and on root systems, leading to increased overstory mortality. Negative effects are also seen on the seed bank of forest floors due to this effect [28].

Simplification of the measurement process could prove helpful especially in areas such as the Netherlands where management and monitoring practices are not as extensive as in the United States. Differentiating between litter and duff layers can often be imprecise and subjective, in most cases depending on the judgement of the individual who is collecting the measurement and making distinctions between litter and duff layers is difficult to do unless in a lab setting where samples can be weighed [29-31]. These layers, even when differentiated in the field, are often mixed not only with each other but with particles from the underlying a horizon [29]. To simplify the process of data collection and potentially reduce error, it is suggested that litter and duff layers be combined into total O-horizon depth when measuring fuels in the Netherlands.

Bulk density is important in determining a fuel bed's ability to ignite and is often used to decide which fuel models a system falls into to calculate important fire behavior variables such as rate of spread, reaction intensity, duff consumption and smoke production and is an especially important variable when predicting the flammability of litter fuels [32-35]. As it is a measure of the compactness of soil, including the O-horizon, bulk density indicates the amount of fuel weight in the fuel bed. Therefore, measuring this parameter will help managers of these fire-prone cover types predict potential risk of wildfire and fire behavior.

Fuel loading across large spatial scales containing many different plant communities can vary greatly due to changes in vegetation composition and structure [27]. In regions where multiple heterogenous systems exist, levels of biomass can differ from each other from cover type to cover type. These differences in fuel loading are also caused by intensity of large-scale disturbances, which can cause variation within a system even on a small scale [36]. Due to these differences between cover types, it can be helpful to the prediction of amount of biomass to analyze them separately. Creating different predictive models for each community helps to give better understanding of the potential fire behavior that managers should expect, which in turn reduces risks that wildfire poses to human-populated areas. This is especially important in countries like the Netherlands, where fragmented landscapes lead to close proximity of human property and living spaces to fire-prone cover types.

Total height and basal diameter of shrubs were shown to be the most significant variables related to predicting total dry weight in each separate cover type. Understanding fuel loads in heather cover types is particularly important, as fire behavior within them can present significant risk to nearby human populations. Not only does this species contain volatile compounds which can lead to higher burn temperatures, it also grows commonly on peatlands, which can often continue to smolder for days following a fire event [37]. In these communities, shrub height has been shown to be useful in predicting fire behavior such as rate of spread [38]. Shrub height is one of several vegetative parameters that can be used to estimate total biomass in these systems. Basal diameter is also integral to estimating fuel loading in similar systems. Small-flowered gorse (*Ulex parviflorus*) is a species that has many comparable qualities to heather, such as being evergreen and accumulating dead biomass that remains part of the living plant's structure. In *U. parviflorus* communities, basal diameter is an important predictor of biomass [39].

Although the results of the shrub fuel analyses were mixed, they can inform management of fire-prone shrublands in the Netherlands in several ways. First, total height and basal diameter should continue to be collected to estimate fuel loading in these shrub communities. Canopy diameter measurements may be useful in future models or other applications, but in the interest of creating a more streamlined methodology for predicting biomass, they can be removed. Furthermore, separation of height measurements into dead heights and live heights would be helpful in better prediction of wildfire effects in heather communities [39]. Dead standing fuels can make already susceptible communities even more hazardous in wildfire events and are therefore important to measure.

A standardized method for detecting downed woody material biomass has existed since the line-intersect sampling method was first introduced in logged forests in New Zealand, and was further refined into the planar intersect method, which utilized numerous shorter transect lines instead of fewer longer ones [22,40,41]. As with most methods of measuring organic matter, there are some potential errors present within line-intersect sampling.

The most major issue is a lack of proper measurement metric for coarse woody debris Downed Woody Material (DWM), such as fallen trees or large downed branches [41]. DWM can vary in shape and position on the landscape, making it difficult to estimate its makeup in the fuel loading of an area. The inclusion of DWM estimation equations could enable a new understanding of the makeup of fuels in a region. In a country with wildfire risk such as the Netherlands, this could be an important factor in estimating biomass fuel loading accurately and precisely [42].

CONCLUSION

Any improvement on estimating fuel loads will provide land managers and emergency agency staff valuable information to make informed decisions. The methods used in this study were effective in assessing litter and duff fuel loads. The challenges in determining fuel loads in shrub dominated environments, and the low accuracy in our results using these methods, suggests that potential fuels by area, rather than individual plant basis, may be more accurate and useful. Future studies might consider assessing similar areas using area as a parameter.

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AUTHOR CONTRIBUTION

All authors contributed towards project conceptualization, design and analysis, and have approved the final manuscript. Lara and Oswald were the primary authors of the manuscript, and the others provided substantial edits to the manuscript.

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CONFLICT OF INTEREST

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