Simple guidelines for northwest European stakeholders to collect fire behavior and fuel moisture data

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1. Fire Behavior

Introduction

The complex interactions between environmental variables and the structure or processes occurring at the fuel level can cause fire to behave in a variety of ways. In general, the main drivers of behavior can be fuel bed structure, slope characteristics, fuel moisture and wind characteristics (Scott, 2012). Depending on the magnitude of each of these variables, fire behavior can be expressed in different dimensions: Rate of spread, Residence time, Flame Length, Heat release, Fireline intensity, among others (Castro Rego et al., 2021). Within these, the most important estimators of the potential damage produced by a fire just after the start of ignition are the Rate of Spread (ROS) and Flame Length (FL) (Cardil et al., 2021). In operational environments, these are very important to measure. As a result, it is critical to make decisions based on a quick and accurate assessment of these variables. It is possible to predict other variables related to fire behavior from rapid field measurements of ROS and FL, which can be a good first perspective of risk conditions for operational planning (Rothermel & Deeming, 1980).

As new fire regions are emerging and so planning and suppression efforts are increasing in these, it is important to share state of the art knowledge from more prepared regions. This article aims to provide basic guidelines on fire behavior concepts. It also aims to describe practical methods for rapidly estimating critical fire behavior parameters in order to quickly qualify and understand the hazard at the start of a fire in the field.

Fire behavior metrics

Rate of spread (ROS)

The most known descriptor of fire behavior is defined as the spread rate in the direction normal to the fire line. In this hypothetical circular-shaped fire, it could be defined as the radial rate of spread, which is the rate of spread in the direction normal to the perimeter at any point (Richards, 1995). It is usually measured in meters or feet per minute. Wind speed, fuel moisture, and terrain slope are the main factors governing the variation of the flame spread rate, according to empirical measurements (Johnston et al., 2008). Given the specific characteristics of the landscape, these variables cause the fire to take different shapes, both on a coarse scale (weather, synoptic conditions) and on a more local scale (terrain, wind direction, fuel moisture). If the fire changes shape, it also indicates that it is spreading at different rates across the landscape, so the most important rate of spread is that of the fire's head, which is usually the fastest.

In a more operational setting, measurements on this variable allow us to project the area burned within a time interval for planning purposes, as well as identify landscape elements at risk. This allows us to manage the types of resources that will be used based on projected losses as the fire burns. The ability to determine evacuation actions is a critical benefit of measuring this variable at the start of a fire.

For a quick field measurement of the rate of spread, two distinguishable elements, such as colored sticks, must be present in the vicinity of the fire. It is important to note that the location chosen for this exercise must consider an a priori assessment of the danger conditions for the personnel. The two distinguishable elements must be separated by a fixed distance in meters and oriented in the same direction as the fire. Wait for the flames to pass through the location where the measurement was taken, and then use an analog or digital device with a stopwatch to time how long it takes to get from one element to the other. Table 1 provides a practical guide for estimating ROS in the field.

Table 1. Practical Guide for On-field measurement of ROS

	Distance [m]			**ROS**
	5 m	10 m	20 m	**[m/min]**
Time [Min′ Sec″]	10′ 00″	20′ 00″	40′	**0.5**
	1′ 40″	3′ 20″	6′ 40″	**3**
	30″	1′ 00″	2′ 00″	**10**
	15″	30″	1′	**20**
	06″	12″	24″	**50**

Flame length (FL)

It is the distance between the flame's tip and the surface of the fuel being burned (Khakzad et al., 2018). It is an important variable to measure because it accounts for the fire's power, providing guidance for various fire management decisions, particularly those pertaining to operational safety. Fires with flame lengths greater than 2.5 meters have been classified as High Intensity and High Danger (Ager et al., 2013; Jahdi et al., 2022).

The tip of the flame is difficult to identify because it is in constant motion and depends on the observer's point of view. This variable can be measured using photographs with a scale within them. Figure 1 depicts the difference between flame length and height, another fire behavior measurement.

Figure 1. Flame Length measurement scheme. Red line indicates Flame Height and Blue line indicates Flame Length

Heat released per unit area (HPA)

Amount of heat emitted per unit area during the flaming phase. It depends on the energy content of the fuels and the amount of fuel being burned at the instant. In general, woody fuels have higher heat content than herbaceous fuels.

$$HPA = H * W$$

H is the amount of energy released per unit mass, dependent on the type of fuel [kJ/kg]
W is the amount of fuel consumed per unit area [kg/m2].

Fireline intensity (FLI)

It is the rate of heat emitted per unit length of the fire front, also known as the Byram fire line intensity. It is expressed in kW/m. It is the indicator that represents much of the information needed for operation simulation or planning. Originally, it is calculated using the following formula:

$$FLI = HPA * ROS$$

HPA is the heat emitted per unit area [kJ/m2] and ROS is the rate of propagation [m/min].

This can be translated as follows: the faster the spread, the less heat directed to the site for the same fireline intensity. Slow-moving fires will concentrate a lot of heat on the site if they have the same fireline intensity as fast-moving fires. If this seems unlikely, keep in mind that the example condition is for the same fireline intensity. not just fast and slow fire.

The physical relationships between different fire behavior parameters, according to Byram (1959), can be reduced to estimate the intensity as a function of flame length. The following equation, according to the scheme and objectives of this work, provides a faster and more practical approach to estimating this in the field.

$$FLI = 259\ FL^{2.17}$$

FL is Flame Length [m]

This provides a practical method for estimating critical fire behavior parameters such as FLI. However, when measuring flame length, it is critical to concentrate on reducing the sources of error.

Fuel Type to Fire Behavior

It is critical to have a perspective on the types of fuels that are distributed, whether for preventive intervention efforts on the landscape or for suppression of active fires. The composition of fuels in the landscape, defined as the variety, abundance, and distribution of fire-prone vegetation, must be considered, and it is the responsibility of wildland fire professionals to relate this to potential fire behavior. Scott and Burgan (2005) described various structural types of fuels, allowing us to associate them with potential fire behavior.

Grass Fuel

Structurally, this type of fuel can vary from grasslands with high grazing intensity to natural grasslands with low or high density. Depending on the case, the speed of fire propagation in this type of ecosystem changes drastically (Cheney et al., 1998), ranging from average speeds and low flame lengths to extreme speeds with long flame lengths, respectively. This depends on the density and length of the grasses.

The behavior is extremely dynamic. The moisture content of fuels has a significant impact on the behavior of this type of vegetation, particularly the rate of spread. In many cases, the sensitivity between these variables explains the abrupt transition from live fuel to death.

Grass-Shrub Fuel

It behaves in a very similar way to herbaceous fuel, it is also sensitive to variations in live fuel moisture, but this sensitivity varies as a function of the relative proportion of grasses and shrubs in the fuel load. The above emphasizes the idea of how important the presence of herbaceous fuel is as a driver of behavior.

Shrub Fuel

The proportion of live or dead branches/leaves, as well as the presence and amount of litter, are the main drivers of fire behavior in this type of fuel. The flame length in this type of fuel is longer, depending on the fuel load, than in herbaceous fuels, but the rate of spread is lower in general.

Timber-Litter Fuel

This case depicts structures with a high concentration of forest and woody material. The amount of dead woody material is the main structural driver in this type of fuel. The influence of live fuel on fire behavior is minimal. When compared to other fuel types, this type has a slower rate of spread and a shorter flame length.

Capacity of Control

Tedim et al. (2018) redefine previous work and classify different types of fires based on how difficult they are to suppress. The latter variable described in this work is a qualitative type of reduction that provides us with a highly useful score for wildland fire crews to assess the hazard.

This approach is practical because it is evaluated in terms of the variables already described above, making it simple to obtain a quick estimate of both hazard and operability for suppression.

Table 2. Thresholds for Capacity of Control Description

Flame Length [m]	Fireline Intensity [kWm^{-1}]	Rate of Spread [m/min]		Capacity of Control
< 1.5	< 500	< 5	< 15 (Grasslands)	Fairly easy
< 2.5	500 – 2,000	< 15	< 30 (Grasslands)	Moderately difficult
2.5 – 3.5	2,000 – 4,000	< 20 (Woodlands)	< 50 (Shrub/Grasslands)	Very diffcult
3.5 -10	4,000 – 10,000	< 50 (Woodlands)	< 100 (Shrub/Grasslands)	Extremely difficult

If values higher than those in the table above are estimated in the field, the fire is classified as an extreme event. Control capacity becomes nearly impossible in these situations. It is critical to consider the difficulty, and especially the impossibility, of carrying out suppression maneuvers, as an indicator within the planning that can be reflected in the reduction of accidents and deaths.

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2. Fuel Moisture

Introduction

Fuel moisture is a primary determinant of fuel flammability, ignition, and rate of spread; therefore, being able to accurately determine fuel moisture content is integral to predicting wildfire danger and behaviour (Matthews, 2014; Scarff et al., 2021). Direct fuel moisture measurements calculated from fuel samples collected in the field are generally considered to provide the most accurate measurements (Matthews, 2010); however, it is important to minimize any introduction of errors through the sampling process. We present here a protocol for collecting fuel moisture data for common northwest European fuel types. These guidelines have been adapted from (Norum & Miller, 1984) and are in line with the protocols used in other northwest European fuel moisture research (e.g., Taylor et al. (2021) and Clay (2022)) to ensure comparability of data collected across stakeholders. Having clear guidelines for collecting field measurements allows potential sources of error to be controlled, and we have modified these guidelines over the course of multiple sampling campaigns with different stakeholder groups to optimize the clarity of instructions. Due to the intensity of collecting fuel moisture measurements, it is not always possible to have one person collecting all the samples and this means sampler bias may need to be accounted for post-collection rather than through sampling design (Supplementary).

Sampling Preparation

The following equipment should first be prepared (Figure 1):

- Aluminum, rust proof, screw lid tins for storing collected samples. Prior to collection tins should be permanently numbered, weighed to the nearest 0.001 g and recorded (tare weight)
- Parafilm for sealing tins
- 2 pairs pruning shears (one for live, one for dead material)
- Soil corer (we use inexpensive apple corers)
- Pen, clipboard and recording sheets
- Laboratory equipment: fine balance (3 dp), drying oven

Samples should be collected as close to the warmest part of the day as possible and between 1100–1700 where samples are collected for fire research or management purposes. This time window allows for morning dew to evaporate and constant humidity levels. Where repeat sampling events are anticipated, samples should be collected as close to the same time as possible, or time-of-day should be accounted for in post-collection analyses as it may contribute to the observed fuel moisture variation.

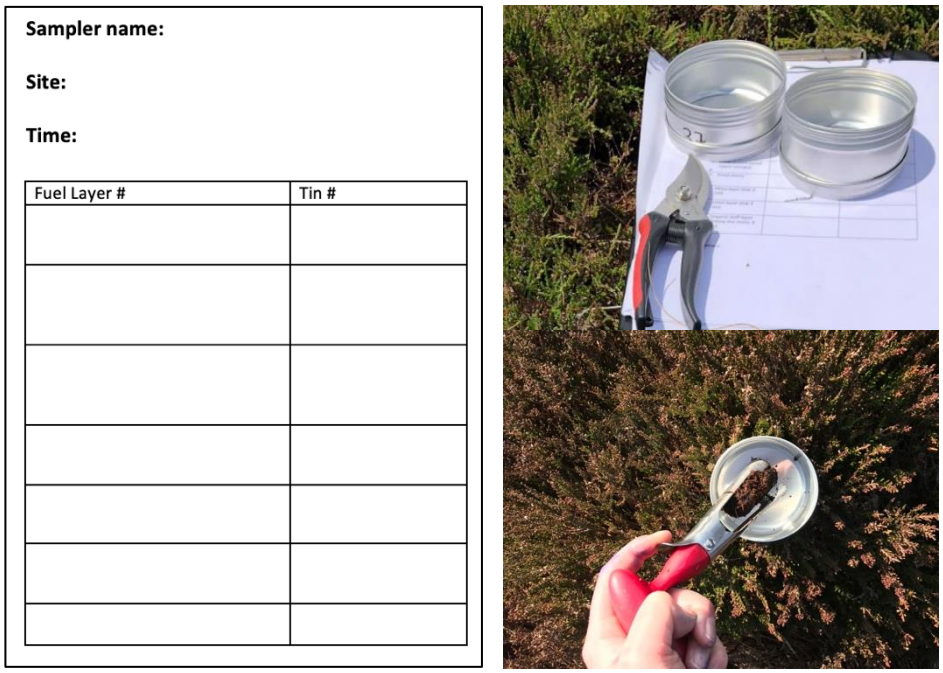

Figure 1: Fuel moisture sampling equipment, including example data sheet (left) and inexpensive soil corer (bottom right) and garden shears (top right).

Fuel Moisture Sampling Procedure

General Procedure

1. On arrival to the sampling site, place sample tins in a shady spot and prepare the data sheet. Record site name, date, time, name of observer and the fuel layers to be collected.
2. Set out a 25 m transect covering a representative area of the sampling site.
3. Using the appropriate equipment, walk along the transect taking the same size sample from each plant in a random manner, one fuel layer at a time (see subsequent sections for specific fuel layers for each fuel type). Try to ensure consistency in the amount of material collected (we suggest filling the tin ¾ full of samples across the full transect).
4. As soon as the material has been collected for one tin, replace the lid tightly and seal it with parafilm. Ensure there is no dirt on the outside of the sample tin.
5. Record the tin number next to the correct fuel layer on the data sheet.

Heather (Calluna vulgaris) Sampling Procedure

Calluna vulgaris is sampled from the following layers of dead and live plants, adapted from (Davies et al., 2010), taken vertically through the centre of the shrub to avoid differences from exposed versus sheltered edges (Figure 2):

1. Live top shoots and canopy
2. Live lower canopy and remaining stems (<0.25-inch diameter)
3. Dead top shoots and canopy
4. Dead lower canopy and remaining stems (<0.25-inch diameter)
5. Moss layer
6. Litter layer
7. Organic layer

Complete steps 1–5 from the general procedure, collecting each fuel layer in step 3 in the following way:

3a. Collect sprigs from approximately 10 live *Calluna* plants randomly along the transect. Clip the sprigs into small one-inch segments, separating the top shoots and canopy into one tin and the lower canopy and remaining stems into another. Try to take the same approximate mass for each sample of the same material
3b. Follow the same process above for dead *Calluna* plants
3c. Collect the top 2 cm of the moss layer by grasping a clump of moss and gently pull them up from the moss layer. Clip off the highly decomposed dark brown moss at the base of the layer
3d. Collect the top 2 cm of the litter layer by collecting the dead litter on top of the soil, found under heather bushes
3e. Using a soil corer, collect 5 samples of the organic layer material along the transect and place into a tin. The organic layer lies below the litter layer and above the mineral soil. It includes litter material that has decomposed to the point that the individual pieces are no longer identifiable. We use the soil corer to extract the top 5 cm of organic material.

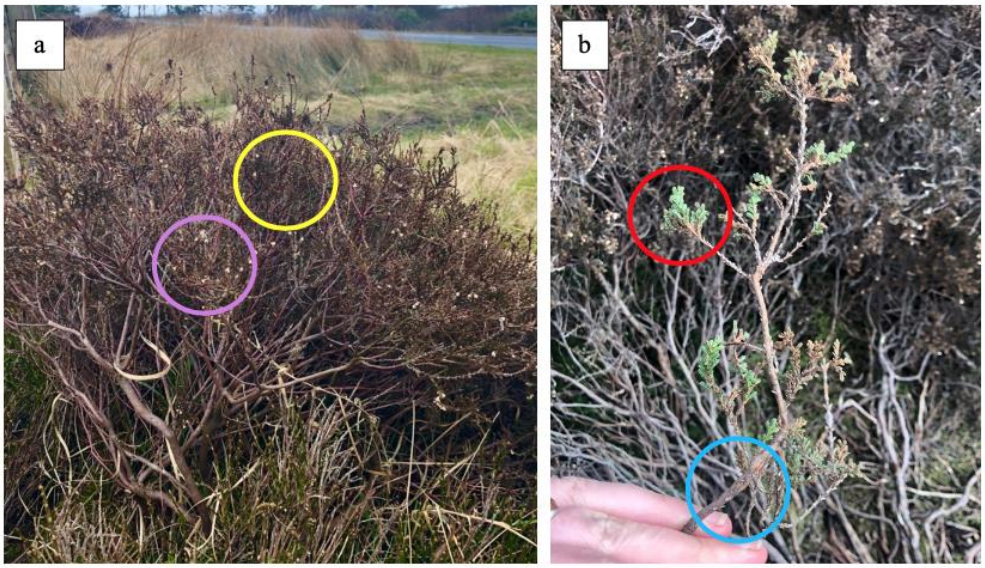

Figure 2: Annotated heather bush (a) showing live (yellow circle) and dead (purple circle) material, and photo (b) of live heather canopy (red circle) and stems (blue circle). Dead heather canopy and stems are the similarly distinguished but for a fully dead section of the plant.

Gorse (Ulex europaeus) Sampling Procedure

Ulex will be sampled from the following layers of live and dead plants (Figure 3):

1. Live canopy
2. Live stems (<0.25-inch diameter)
3. Dead canopy
4. Dead stems (<0.25-inch diameter)
5. Litter layer

Complete steps 1–5 from the general procedure, collecting each fuel layer in step 3 in the following way:

3a. Collect samples from 10 live gorse plants randomly along the transect. Clip the samples into small one-inch segments, separating the canopy from the stems in two tins. Try to take the same approximate mass for each sample of the same material
3b. Follow the same process above for dead gorse
3c. Collect the top 2 cm of the litter layer by collecting the dead litter on top of the soil, found under gorse bushes

Figure 3: Gorse bush (a) showing live (yellow circle) and dead (purple circle) material, and examples (b) of gorse live canopy (red) and live stems (blue). Dead canopy and stems are similarly distinguished but for a fully dead section of the plant.

Bracken (Pteridium aquilnum) Sampling Procedure

Bracken is sampled from the following fuel layers of live and dead plants:

1. Live stems
2. Live leaves
3. Dead stems
4. Dead leaves

Complete steps 1–5 from the general procedure, collecting each fuel layer in step 3 in the following way:

3a. Collect samples from 10 live bracken plants randomly along the transect. Clip the stems and leaves into small one-inch segments, separating them in two tins (Figure 4). Try to take the same approximate mass for each sample of the same material

3b. Follow the same process above for dead bracken

Molinia Sampling Procedure

Live and dead *Molinia* is collected following steps 1–5 in the general procedure. Live *Molinia* (live blades) and dead *Molinia* (dead blades) are collected in separate tins (Figure 4).

Forest Litter Sampling Procedure

Fine forest litter is sampled from the following fuel layers:

1. Forest mixed leaf litter
2. Dead twigs
3. Organic material

Complete steps 1–5 from the general procedure, collecting each fuel layer in step 3 in the following way:

3a. Collect 10 samples of mixed leaf litter along the transect from the forest floor, taking care to only pinch the litter and not take any organic material

3b. Collect approximately 20 samples of dead twigs of the same size along the transect. Clip the twigs into one-inch segments in one tin. Take samples from material resting on the ground but do not collect twigs directly touching/buried in litter, organic material or soil. Each sample must be detached from its growth point and less than 0.25-inches in diameter.

3c. Using a soil corer, collect 5 samples of the organic layer material along the transect and place into a tin. The organic layer lies below the litter layer and above the mineral soil. It includes litter material that has decomposed to the point that the individual pieces are no longer identifiable. We use the soil corer to extract the top 5 cm of organic material.

Laboratory Procedure

1. Preheat drying oven to 80 °C
2. Remove parafilm from tin lid, ensure no tape or debris is stuck to the tin
3. Weigh the tin (keep the lid on) to 3 dp and record this value as the wet weight. Reset the scales to zero before each sample is weighed.
4. Weigh all of the samples in this manner.
5. Remove the lid and place it under the tin as you put the sample in the drying oven. Space the samples evenly in the oven so air can circulate around the tins (Figure 4). Record the date and time the samples were put in the oven.
6. Dry the sample for at least 48 hours at 80 °C.
7. At the end of the drying time, take samples from the oven in batches, quickly replacing the lid tightly as each tin is removed to prevent absorption of moisture by air. Close the oven door in between removing samples from the oven.
8. Allow the tins to cool to room temperature before reweighing them (as outlined in step 3) and record the dry weight on the laboratory sheet.
9. Calculate percentage of dry moisture content as per Equation 1.

Fuel moisture content: the ratio of the weight of the water contained to the dry weight of the material, expressed as a percentage.

$$\frac{(sample\ wet\ weight - sample\ dry\ weight)}{sample\ dry\ weight - container\ tare\ weight}\ (100) \qquad 1$$

10. After fuel moisture content has been calculated and odd values have been rechecked, discard the sample and clean the tins for reuse. Leave to air dry completely before replacing lids and storing.

Fig. 1a Dead bracken stems

Fig. 1b Dead bracken leaves

Fig. 2a Live heather canopy

Fig. 2b Dead heather canopy

Fig. 2c Dead heather stems

Fig. 3a Dead gorse canopy

Fig. 3b Dead gorse stems

Fig. 4c Gorse litter

Fig. 5 Dead *Molinia*

Figure 4: Examples of common northwest European fuel samples.

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Supplementary

Accounting for sampler bias improves confidence in fuel moisture content field measurements

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Introduction

Fuel moisture is a primary determinant of fuel flammability, ignition and rate of spread; therefore, being able to accurately determine fuel moisture content is integral to predicting wildfire danger and behaviour (Matthews, 2014; Scarff et al., 2021). Where feasible, direct measurements of fuel moisture content are generally preferred; however, large-scale sampling campaigns are intensive and can require a lot of people to adequately represent the variability across the research area (Matthews et al., 2010). Where direct measurements are not feasible, various models have been developed to indirectly monitor fuel moisture, particularly across long time periods (e.g., Cawson et al., 2020; Miller et al., 2022). While we routinely quantify sources of uncertainty associated with fuel moisture models, field-based fuel moisture measurements also include uncertainties within their measured values. It is important to be able to extract values of fuel moisture from other sources of variability to optimise accuracy of measurements and isolate the underlying controls of interest. In doing so, we improve our scientific understanding of fuel moisture variability and our ability to accurately model fuel moisture for fire management.

Sampler bias in fuel moisture monitoring

Where fuel moisture campaigns require multiple samplers to collect fuel samples, between-sampler differences (referred to here as sampler bias) become a relevant source of variability in measurements. The importance of human bias in field surveys has been reported in other environmental studies, particularly citizen science projects measuring species presence-absence and quantifying percentage cover (Morrison (2016) and references therein). Between-sampler differences in fuel moisture measurements can arise through different levels of experience, motivation and interest and consequent variation in sampling effort. This bias is influenced by time. Previous citizen science research, particularly over longitudinal studies, report a "learner effect", where volunteers show improvements in their data collection abilities over time (Dickinson et al., 2010). However, the effect of time can also be negative, as physical and mental fatigue can create variation in sampling effort (Moore et al., 2011). Some sources of sampler bias can be controlled through careful sampling design but sampler bias cannot be completely prevented as individuals following the same protocol are naturally likely to interpret instructions differently, and this bias is incorporated into the resulting measurements. Fuel moisture measurements that do not account for sampler bias are less accurate as there is no way to extract the measurement from the overall random error (Bird et al., 2014; August et al., 2020).

Research questions

We conducted an intensive fuel moisture sampling campaign to assess the influence of sampler bias on direct fuel moisture measurements of *Calluna vulgaris* within a temperate fire-prone landscape. The complexity of live fuel moisture in temperate environments is not well represented by existing fuel moisture models so this research aids efforts to isolate the processes that influence fuel moisture within these landscapes. However, this approach is more broadly applicable for estimating the sampler error in fuel moisture measurements and enabling a confidence range to be applied to estimates used in a practical setting. Accounting for sampler bias also opens opportunities for large-scale fuel moisture monitoring campaigns using citizen science, which is necessary for understanding fuel moisture dynamics at regional and national scales. To this end, we address the following research questions: (1) to what extent do between-sampler differences influence fuel moisture variability at the plot scale? (2) Is the influence of sampler bias time and/or fuel layer dependent?

Methods

Study site

The field campaign was completed by an undergraduate geography field class (n = 17) in the Lickey Hills Country Park, Birmingham, England. This site was selected as it is representative of the type of heathland landscapes that are found throughout temperate, fire-prone environments. Two *Calluna*-dominated plots were selected, and samplers were evenly split across the two plots to minimise overall destruction of *Calluna* in one location. The two plots were both situated on a hillslope on the same soil type within Lickey Hills and contained mainly *Calluna* with patches of bracken interspersed.

Fuel moisture sampling campaign

A sample set comprised seven *Calluna* fuel layers: live canopy; live stems; dead canopy; dead stems; moss; litter; and organic layer (top 5 cm of organic material above mineral soil). Each sampler collected one set of samples every hour between 1000 and 1800, resulting in nine samples per sampler and a total of 1071 samples overall. None of the samplers had monitored fuel moisture before, and all samplers received the same protocol adapted from Norum & Miller (1984), a briefing prior to beginning sampling and advice during the first hour of sampling to ensure correct species identification and sample size for laboratory analysis. Briefly, each sampler randomly collected fuel clippings across the entire plot area (ca. 10 different plants) to ensure samples captured within-plot variability. We stored clippings in an aluminium tin with a screw-fit lid sealed with masking tape.

We calculated gravimetric fuel moisture content (mass of water per mass of sample, %) following Norum & Miller (1984). We weighed the tinned samples (wet weight) as soon as possible the morning after collection. We then dried the samples for at least 48 h at 80 °C and reweighed them (dry weight).

Data analysis

The distribution of fuel moisture content for all fuel layers except for moss and organics were sufficiently similar between the two sampling plots to analyse all the samplers together. We analysed the moss and organic layer fuel moisture measurements separately for each plot to account for between-plot variability in these fuel layers. We used quadratic mixed effects models to analyse the random effect of sampler on fuel moisture variation with time as the fixed effect. We calculated the model marginal R^2 (variation explained by the fixed effects) and conditional R^2 (variation explained by both fixed and random effects). The difference represents the amount of variation explained by sampler bias. The standard deviation of the random effect can be interpreted as a confidence range to adjust fuel moisture

estimates to account for between-sampler differences. We conducted all statistical analyses in R version 4.1.2 (R Core Team, 2022) using packages lme4 (Bates et al., 2015) and MuMIn (Bartoń, 2022).

Results

Between-sampler fuel moisture variability

Between-sampler differences led to high variability in fuel moisture content measurements across all fuel layers and time steps (Figure 1). Individuals sampling within the same plot at the same time obtained different fuel moisture content measurements up to a maximum range of 313% (moss plot A), 297% (organic plot A), 249% (litter), 210% (organic plot B), 105% (moss plot B), 76% (live canopy), 73% (dead canopy), 68% (dead stems) and 39% (live stems). Most fuel layers had a low-end distribution of median fuel moisture content, with a high upper quartile, upper extreme and high fuel moisture outliers. Live *Calluna* had more of an even distribution of above and below median fuel moisture content measurements.

There was no obvious diurnal pattern in sampler variability across the day for any of the fuel layers. However, median live and dead *Calluna* fuel moisture content was highest at 1000 and generally decreased throughout the day before starting to increase again at the end of the sampling period. This diurnal pattern was not evident in the wettest fuel layers.

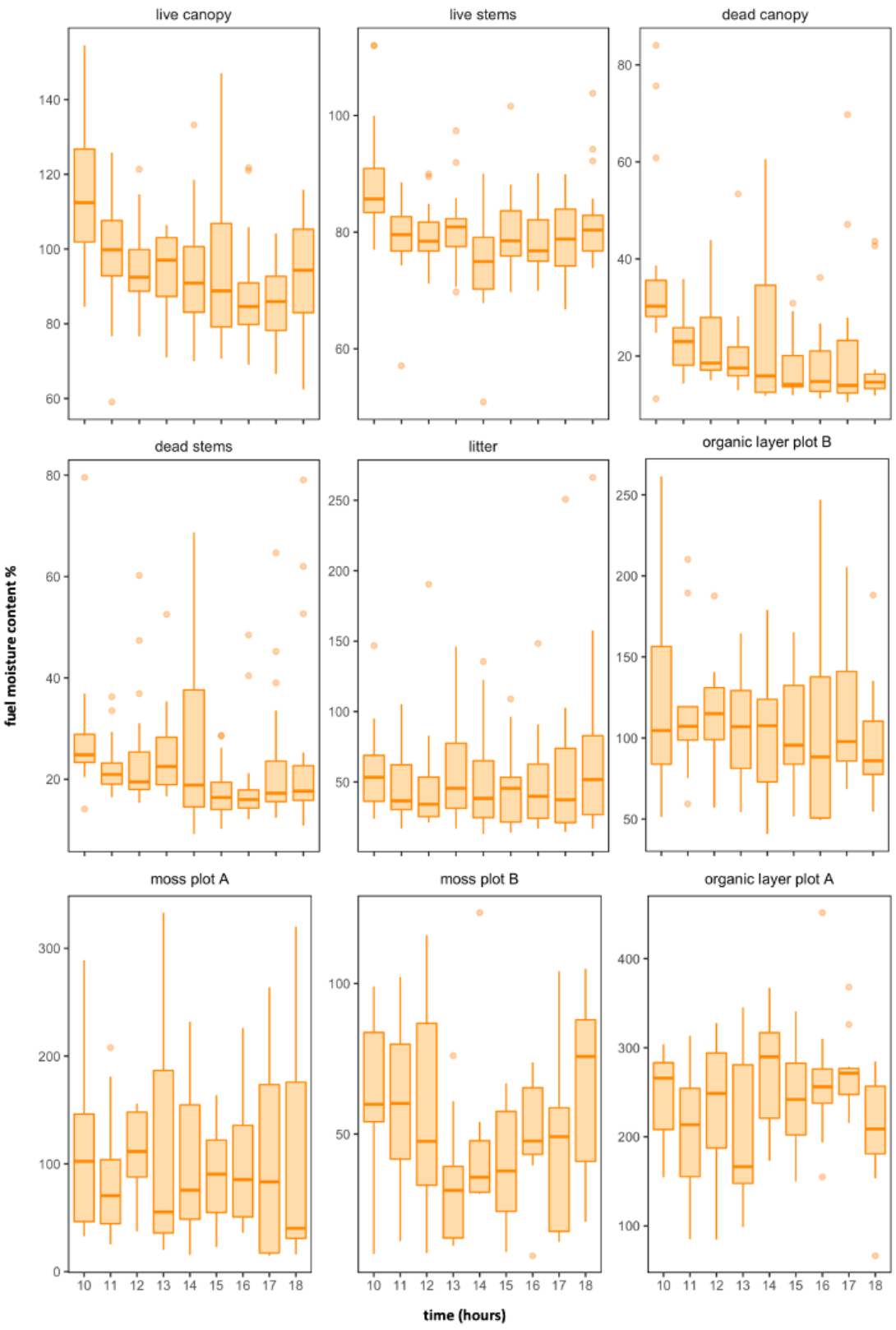

Figure 1: Sampler variability in fuel moisture content measurements for each fuel layer hourly from 1000 to 1800.

Table 1: Summary statistics from the mixed effects model of diurnal fuel moisture variability with sampler as a random effect.

Fuel layer	Marginal R^2%	Conditional R^2%	Coefficient of variation	SD of the random effect
live canopy	17.92	37.09	0.07	7.61
live stems	13.00	32.82	0.04	3.64
dead canopy	13.06	14.33	0.04	1.47
dead stems	1.75	5.65	0.10	2.65
moss A	0.07	6.97	0.20	21.81
moss B	10.27	36.68	0.21	14.64
litter	2.04	46.12	0.48	27.44
organic A	2.10	7.62	0.08	17.83
organic B	1.38	35.23	0.23	28.43

We used mixed effect models to examine the influence of time-of-day (marginal R^2) and sampler bias (difference between conditional and marginal R^2) in explaining the overall model (conditional R^2) variation in fuel moisture. Time-of-day has a similar influence on *Calluna* canopy fuel moisture, regardless of whether the canopy material is live or dead. However, samplers are substantially more consistent in sampling dead *Calluna* than live *Calluna*. Between-sampler differences contribute to explaining 19% of the measured live fuel moisture variability. With the exception of the dead canopy, sampler bias explains more fuel moisture variability than time-of-day. Sampler bias is greatest in litter samples (44% variation explained) overall and organics (34%) and moss (26%) at plot B. These fuel layers also have a high coefficient of variation but the two are not always analogous. Dead stems fuel moisture has a coefficient of variation of 0.1 despite a high degree of consistency between different sampler measurements. Conversely, the coefficient of variation of live *Calluna* is lower than dead stems while between-sampler variability is substantially higher.

The standard deviation of the sampler effect gives an estimate of the range of confidence in fuel moisture values as a result of between-sampler differences. Live canopy *Calluna* fuel moisture content measurements could be roughly expected to range 8% above or below the actual measurement, due to between-sampler differences. This range is up to ±27% for litter samples.

Discussion

Quantifying sampler bias in fuel moisture estimates

Seventeen samplers collecting fuel moisture samples at the same time within the same site measured very different fuel moisture contents. With the exception of dead canopy material, sampler bias was more important than time-of-day in explaining fuel moisture variation at the plot scale. Significant attention is given to diurnal fuel moisture variability in rapidly drying fine fuels (e.g., Slijepcevic et al., 2013; Bilgili et al., 2019; Zhang & Sun, 2020); however, we have shown that sampler bias can exceed diurnal drying patterns and should also be considered in fuel moisture dynamic studies. Previous species identification citizen science studies observed a temporal pattern in observer bias related to both increasing experience (Dickinson et al., 2010) and fatigue (Morrison, 2016), but we did not observe any consistent trend in sampler bias through the sampling period.

Sampler differences explained the greatest amount of variation in litter material, followed by organics and moss at plot B and live *Calluna*. Importantly, it is not exclusively high absolute values of fuel moisture that are associated with large between-sampler differences. Fuel layers that are harder to sample and require more subjective decision-making by the sampler may result in greater sampler bias. Even with protocols and training, subjective decision-making and variation in sampling effort influences sampler bias in these layers. For instance, samplers must identify the top 2 cm of moss and litter material, remove any attached decomposing material and ensure fuel sample separation where litter material is interspersed in patches of moss. Samplers were also highly inconsistent in sampling live *Calluna*. Subjectivity in clipping live *Calluna* can incorporate sampler bias in the length of sprigs collected, where samplers choose to separate the live canopy from the live stems and even correctly identifying live from dead *Calluna*. A lack of confidence in the latter could lead to subconscious targeting of the greenest live material and missing the brown live material that is harder to identify.

At the other end of the scale, samplers were highly consistent in sampling dead *Calluna* but the coefficient of variation was higher than expected for having low sampler bias. This is attributable to outliers resulting from the misidentification of live *Calluna* as dead. Where dead fuel is correctly identified, this material is easy to collect following the sampling protocol and sampler bias is low. Sampler bias in this case is mainly a concern where brown *Calluna* is incorrectly identified as dead. Where dead fuel moisture is the most important variable, sampler bias may be less important to account for than time-of-day and illogical values from misidentifications can be filtered out of the dataset.

Individual sampling patterns throughout the day reflected three different types of sampler bias (data not shown): those who were consistently extreme (i.e., samples were always wetter or drier than average); those who were consistent overall (i.e., samples were around the average fuel moisture throughout the day); and those who

were inconsistently extreme (i.e., samplers had both the driest and wettest samples from hour to hour).

From the results of this campaign, we identify a rough confidence range that can be applied to fuel moisture measurements to account for the uncertainty associated with between-sampler differences. These adjustments may be useful in practical applications, particularly where there is long-term, irregular fuel moisture sampling carried out by different individuals. It may be beneficial for decision making to give a range of values of fuel moisture content that will be more accurate than a single value, knowing that different samplers inherently introduce bias into measurements.

Controlling for sampler bias through sampling design

Carefully considered sampling protocols can minimise sources of sampler bias prior to field collection (Dickinson et al., 2010; Morrison, 2016). We reduced sampling effort variability by having a clear protocol for where, when and how samples were to be collected. We also controlled for between-sampler differences by recruiting volunteers from the same cohort with no prior fuel moisture sampling experience and provided them with the same level of training

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Accounting for sampler bias in data analysis

Where sources of bias cannot be controlled through experimental design, statistical tools can be used to remove sampler bias from other sources of error (Bird et al., 2014; August et al., 2020). Statistical models such as mixed effects models (Aagaard et al., 2018) and machine learning tools like boosted regression trees (Cox et al., 2012), random forests and artificial neural networks (Fink & Hochachka, 2012) have been used in citizen science ecological studies. In this field campaign, we have used mixed effects models to fit sampler as a random effect. Mixed effects models are useful for quantifying the contribution of sampler bias and isolating this bias from variables of interest and overall error. Mixed effects models require equal sample sizes from each individual sampler, so this method is most useful when considered at the sampling design stage or when the dataset is sufficiently large to filter (Zuur et al., 2010).

Larger fuel moisture sampling campaigns than implemented here may require greater flexibility in where and when samples are collected and who is recruited to collect samples. In these situations, the collection of sampler metadata (e.g., sampler experience, training received and profession (e.g., heathland land managers may have greater familiarity and confidence in identifying fuel layers than others)) can help to account for between-sampler differences. Fuel moisture samples should have a sampler identifier to relate metadata metrics to fuel moisture content and can be used to control sampling designs to prevent confounding with covariates, filter databases for analyses and include metrics in models to isolate fuel moisture measurements from sources of sampler bias (August et al., 2020).

Citizen science for fuel moisture monitoring

Accounting for sampler bias allows us to utilise citizen science approaches to scale up field studies to understand fuel moisture dynamics at broad spatiotemporal scales that cannot be captured by traditional, controlled field experiments (Dickinson et al., 2010). This is important for developing robust fuel models and is especially important in environments where cross-scale fuel moisture dynamics are not fully understood. Considering potential sampler bias sources prior to conducting large-scale fuel moisture campaigns can allow for targeted collection times, locations and sampler metadata to isolate spatiotemporal trends in fuel moisture variability.

Implications

Sampler bias can lead to high variability in fuel moisture content measurements within the same plot, fuel layer and time of day. With this knowledge, we can give a range of confidence in fuel moisture estimates associated with sampler bias that will be more accurate than a single value. If sampler bias is not accounted for in fuel moisture studies, then it adds to the overall model error and may obscure important trends and dynamics. It is therefore important to isolate this bias to develop fuel moisture models, improve the accuracy of fuel moisture measurements and upscale fuel moisture monitoring campaigns.

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