CSIRO PUBLISHING

RESEARCH NOTE
https://doi.org/10.1071/WF23078

International Journal of WILDLAND FIRE
International Association of Wildland Fire

Accounting for among-sampler variability improves confidence in fuel moisture content field measurements

Kerryn Little[A,*], Laura J. Graham[A,B] and Nicholas Kettridge[A]

For full list of author affiliations and declarations see end of paper

*Correspondence to:
Kerryn Little
School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham, UK
Email: k.e.little@bham.ac.uk

Received: 2 December 2022
Accepted: 30 November 2023
Published: 21 December 2023

Cite this:
Little K *et al.* (2024)
International Journal of Wildland Fire **33**, WF23078.
doi:10.1071/WF23078

ABSTRACT

Background. Direct fuel moisture content measurements are critical for characterising spatio-temporal variations in fuel flammability and for informing fire danger assessments. However, among-sampler variability (systematic differences in measurements between samplers) likely contributes to fuel moisture measurement variability in most field campaigns. **Aims.** We assessed the magnitude of among-sampler variability in plot-scale *Calluna vulgaris* fuel moisture measurements. **Methods.** Seventeen individuals collected samples from six fuel layers hourly from 10:00 hours to 18:00 hours. We developed mixed effects models to estimate the among-sampler variability. **Key results.** Fuel moisture measurements were highly variable between individuals sampling within the same plot, fuel layer, and time of day. The importance of among-sampler variability in explaining total measured fuel moisture variance was fuel layer dependent. Among-sampler variability explained the greatest amount of measurement variation in litter (58%) and moss (45%) and was more important for live (19%) than dead (4%) *Calluna*. **Conclusions.** Both consideration of samplers within the experimental design and incorporation of sampler metadata during statistical analysis will improve understanding of spatio-temporal fuel moisture dynamics obtained from field-based studies. **Implications.** Accounting for among-sampler variability in fuel moisture campaigns opens opportunities to utilise sampling teams and citizen science research to examine fuel moisture dynamics over large spatio-temporal scales.

Keywords: *Calluna vulgaris*, citizen science, diurnal, ecological field studies, fuel moisture dynamics, heathland, measurement error, mixed effects models, spatiotemporal variation, wildfire.

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 (Scarff *et al.* 2021; Ellis *et al.* 2022; Dickman *et al.* 2023). Field-based sampling of fuels provides the only direct measure of fuel moisture content. However, fuel moisture contents vary both rapidly in time through the day in response to humidity fluctuations (Matthews 2014) and over long time periods in response to seasonal and interannual weather patterns (Pivovaroff *et al.* 2019; Brown *et al.* 2022). Fuel moisture contents also likely vary over a range of spatial scales (plot – landscape – regional) in response to diverse ecohydrological and climatological controls (Nyman *et al.* 2018; Nolan *et al.* 2022*a*). Intensive large-scale and long-term sampling campaigns with a large number of people are necessary to adequately sample this complex spatio-temporal variability in fuel moisture contents, particularly to sample spatial variability in fuel moisture across extensive research areas during short periods of consistent fire weather conditions (Matthews *et al.* 2010).

In these large fuel moisture measurement campaigns, there are two key sources of variability in the sampling process: (1) random sampling error, where different plants or parts of the plant from the appropriate layer are selected; and (2) sampler error; for example, where a sampler consistently has a different interpretation of a fuel layer.

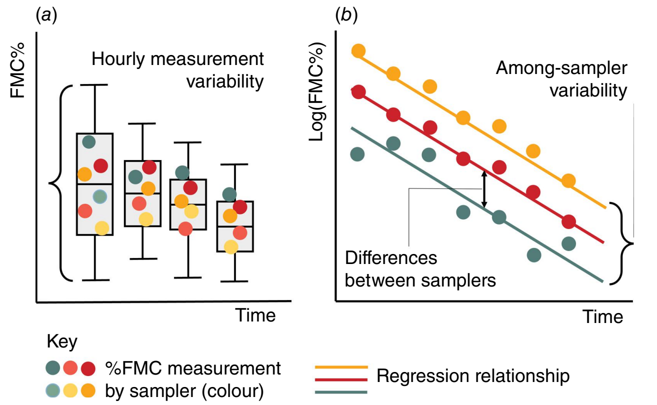

Fig. 1. Schematic diagram outlining definitions of variability. (*a*) 'Hourly measurement variability' is the variation in the moisture content measurement of a given fuel layer in each hour. This results from both among-sampler variability and random sampling error in the plot. (*b*) 'Among-sampler variability' is variability due to systematic differences between samplers that occur across repeated measurements during the day.

Because the error associated with (1) is random, it can be averaged out through repetition. However, (2) is systematic and likely becomes a relevant source of measurement error. We define this as 'among-sampler variability' within the text (systematic differences in fuel moisture content measurements between samplers; Fig. 1).

Where direct measurements are not feasible, various models have been developed to indirectly estimate 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 (Lai *et al.* 2022), field-based fuel moisture measurement errors are rarely considered explicitly. To improve fuel moisture experimental designs and analyses it is important to be able to extract among-sampler variability from other sources of fuel moisture measurement variability. In doing so, we improve our scientific understanding of fuel moisture contents and our ability to accurately simulate its values for fire management.

Citizen science for fuel moisture monitoring

Citizen science is a powerful approach for collecting large quantities of environmental data and is critical for understanding processes operating across large spatio-temporal scales (Devictor *et al.* 2010; Isaac *et al.* 2014). Among-sampler variability is inherent in field studies involving multiple individuals, as people naturally carry out tasks differently, and can arise through different levels of experience, motivation, and different interpretations of protocols. The importance of among-sampler variability has been reported in previous environmental citizen science projects, particularly for studies monitoring species presence-absence and quantifying flora percentage cover (e.g. Morrison 2016 and references therein; Sicacha-Parada *et al.* 2021; Nolan *et al.* 2022*b*). Some sources and impacts of among-sampler variability can be lessened through careful experimental design (e.g. developing effective training protocols, recruiting individuals with similar levels of prior experience). However, among-sampler variability cannot be completely eliminated, and this error is incorporated into the resulting measurements (Bird *et al.* 2014; August *et al.* 2020).

Accounting for among-sampler variability allows us to optimise citizen science opportunities to understand fuel moisture dynamics at broad spatio-temporal scales that cannot be captured by traditional, controlled field experiments (Dickinson *et al.* 2010; Arazy and Malkinson 2021). 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 among-sampler variability prior to conducting large-scale fuel moisture campaigns can allow for targeted collection times, locations, and sampler metadata to isolate spatio-temporal fuel moisture dynamics.

Research questions

We conducted an intensive sampling campaign to determine the magnitude of among-sampler variability in measured fuel moisture at the plot scale within a *Calluna vulgaris* dominated temperate fire-prone landscape (cf. Davies *et al.* 2010). Our findings are widely applicable for estimating among-sampler variability in fuel moisture measurements and enabling a confidence range to be applied to estimates used in a practical setting. Accounting for among-sampler variability also opens opportunities for large-scale fuel moisture monitoring campaigns using citizen science, which are necessary for understanding fuel moisture dynamics at regional and national scales.

Materials and methods

Study site

The field campaign was completed by an undergraduate geography field class ($n = 17$) in the Lickey Hills Country Park, Birmingham, England (52.3723°N, 2.0045°W). The site was selected as it is representative of the type of heathland landscapes that are found throughout temperate fire-prone environments (Glaves *et al.* 2020). Two *Calluna vulgaris*-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 ~300 m^2 situated on hillslopes on the same shallow, acidic, peaty soils (Farewell *et al.* 2011) ~1000 m apart. Plots were dominated by *Calluna* and interspersed with *Vaccinium myrtillus* (common bilberry) and *Pteridium aquilinum* (bracken).

Fuel moisture sampling campaign

Students sampled six *Calluna* fuel layers each hour (Fig. 2). These layers were: live canopy; live stems; dead canopy; dead stems; surface moss (*Kindbergia praelonga* dominant species); and surface litter. Each sampler collected one set of samples every hour between 10:00 hours and 18:00 hours, resulting in nine sets of samples per sampler and a total of 918 samples overall. None of the samplers had monitored fuel moisture before, and all samplers received the same protocol (see Supplementary Material and Fig. S1) adapted from Norum and Miller (1984). We provided 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. Each sampler was instructed to haphazardly collect fuel clippings from each fuel layer across the entire plot area (~ 10 different plants) in accordance with Norum and Miller (1984). The undergraduate students stored clippings in an aluminium tin with a screw-fit lid sealed with masking tape. We calculated gravimetric fuel moisture content (FMC, mass of water per mass of dried sample, %) following Norum and 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). All fuel moisture contents are presented throughout as percentages; mass of water as a percentage of the mass of the dried sample (%).

Data analysis

We used mixed effects models with time as a fixed effect and sampler identity as a random effect. By including sampler as a random effect, this allowed us to estimate the among-sampler variability (Fig. 1), where the actual identity of the sampler is not important. The standard deviation of the random effect can be interpreted as the among-sampler variability once fixed effects (in this case time of day) have been accounted for. We also calculated the coefficient of variation (standard deviation of the random effect divided by the mean FMC% for a given layer) to facilitate comparability across fuel layers of different fuel moisture content ranges.

Finally, 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) (Nakagawa and Schielzeth 2013). The difference represents the amount of variation explained by among-sampler variability, and therefore gives an understanding of how important accounting for among-sampler variability is for a given layer. 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

Fuel moisture measurement variability

High fuel moisture content measurement variability was observed across all fuel layers (Fig. 3). Individuals sampling within the same plot at the same time obtained different fuel moisture content measurements up to a maximum range of 320% (moss), 249% (litter), 76% (live canopy), 72% (dead canopy), 68% (dead stems), and 39% (live stems). Most fuel layers had a right-skewed distribution of measured 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 measured fuel moisture content. Measured live and dead *Calluna* fuel moisture content was highest at 10:00 hours 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 (Fig. S2).

Among-sampler variability in fuel moisture content

Among-sampler variation, measured as the standard deviation of the random effect, ranged from 1.25 (dead canopy

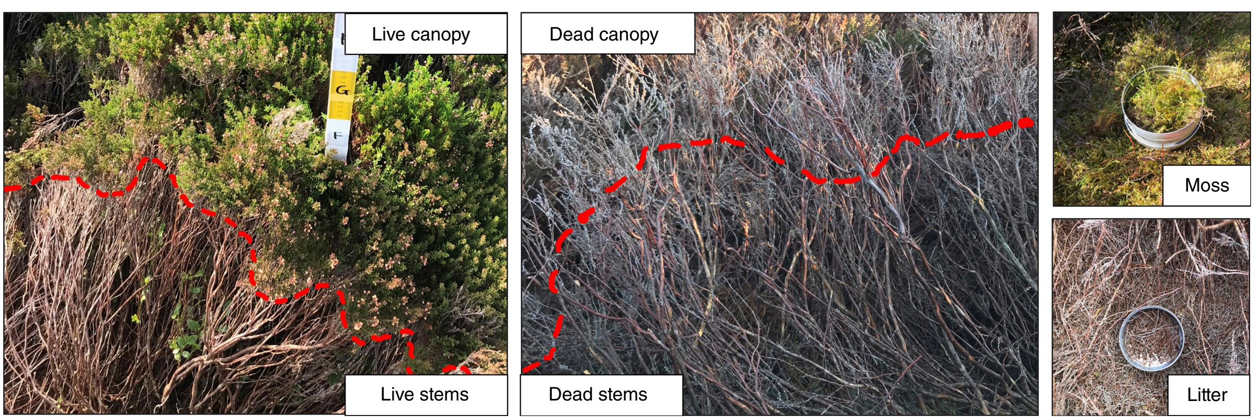

Fig. 2. Visual depiction of the six different fuel layers sampled by the students each hour through the sampling period. Red line depicts the boundary between the canopy above and the stems below (Photo credit: Kerryn Little).

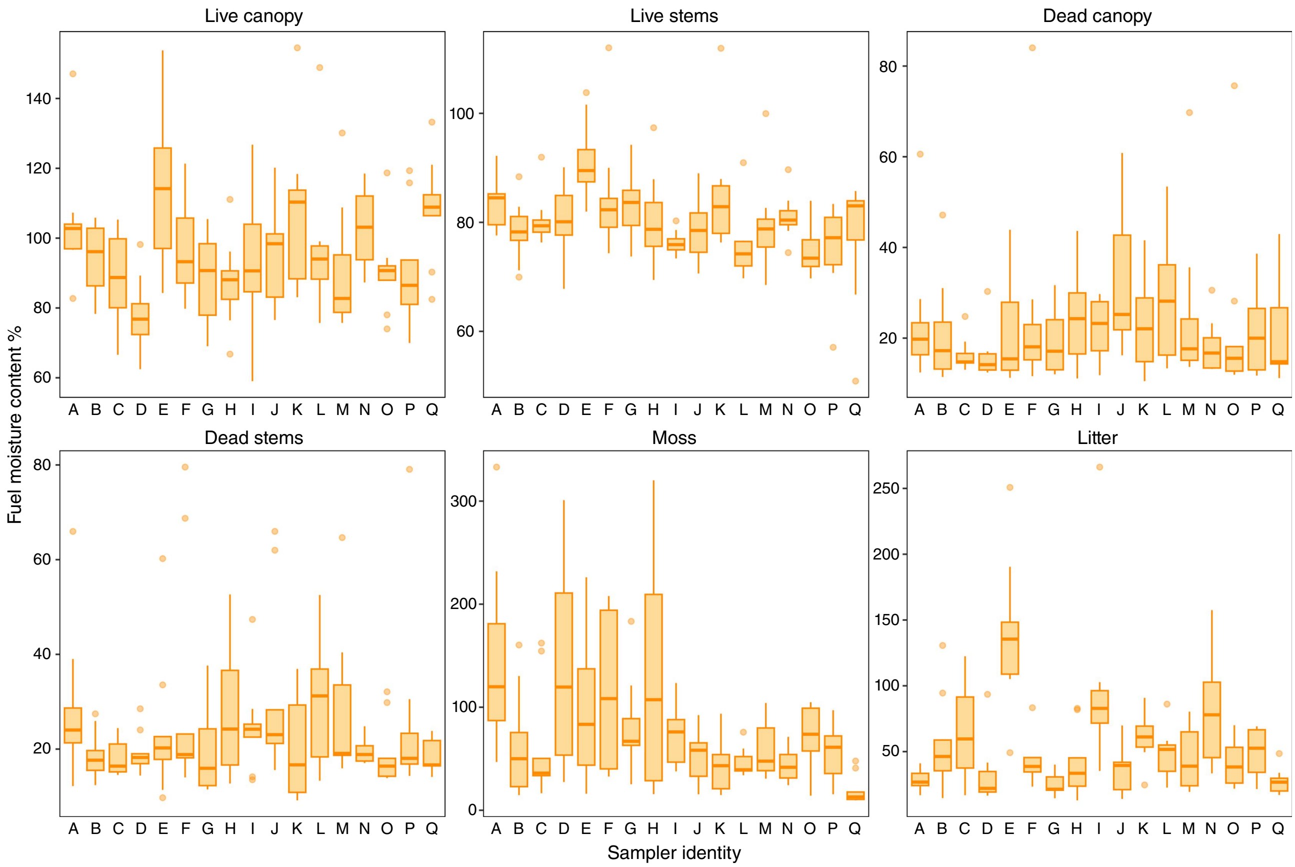

Fig. 3. Measurement variability in fuel moisture content measurements collected by each sampler from 10:00 hours to 18:00 hours by fuel layer. Each *y*-axis is scaled independently to clearly visualise within-fuel layer measurement variability.

Table 1. Summary statistics from the mixed effects model of diurnal fuel moisture content (FMC) measurement variability with sampler as a random effect.

Fuel layer	s.d. of the random effect (raw among-sampler variability in FMC%)	Coefficient of variation (relative among-sampler variability in FMC%)	Estimate of time of day (s.e.)	Marginal R^2	Conditional R^2	Difference
Live canopy	7.48	0.07	−2.45 (0.44)	0.14	0.32	0.18
Live stems	3.51	0.04	−0.47 (0.22)	0.02	0.21	0.19
Dead canopy	1.25	0.04	−1.59 (0.38)	0.10	0.11	0.01
Dead stems	2.63	0.10	−0.53 (0.40)	0.01	0.05	0.04
Moss	32.13	0.40	−0.64 (1.79)	<0.01	0.45	0.45
Litter	27.37	0.56	1.19 (0.95)	<0.01	0.58	0.58

Values represent fuel moisture contents as percentages; mass of water as a percentage of the mass of the dried sample (%).

layer) to 32.13 (moss layer). Because each layer has a very different mean value for FMC%, we also present the coefficient of variation, which allows us to provide relative estimates of among-sampler variation. These range from 0.04 (live stems and dead canopy) to 0.56 (litter layer). In general, among-sampler variation is larger in the wetter layers (moss and litter) (Table 1). The amount of variance explained by the random effects (conditional R^2 – marginal R^2) can provide us with information about how important it is to take account of the among-sampler variability. This was greater than the amount of variation explained by the fixed effects for all layers except dead canopy, suggesting it is crucial to account for among-sampler variability in such studies. It should be noted, however, that the R^2 values are sensitive to the sample size and study specifics. Time of sampling explained up to 14% (live canopy layer) of the variability in the data.

Discussion

Quantifying among-sampler variability 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, among-sampler variability was more important than time-of-day in explaining the total measured fuel moisture variation of each fuel layer at the plot scale. Significant attention is given to diurnal variability in fuel moisture content in rapidly drying fine fuels (e.g. Slijepcevic *et al.* 2013; Bilgili *et al.* 2019; Zhang and Sun 2020). However, we have shown that among-sampler variability can exceed diurnal drying patterns and should also be considered in fuel moisture dynamics studies.

Among-sampler variability explained the greatest amount of variation in litter fuel moisture, followed by moss and live *Calluna* stems and canopy. Importantly, it is not exclusively the highest absolute values of fuel moisture that are associated with large among-sampler variability. We hypothesise that some fuel layers are harder to sample and require more subjective decision-making by the sampler. Even with protocols and training, any such subjective decision-making and variation in sampling effort will produce among-sampler variability in fuel 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. Subjectivity in clipping live *Calluna* can also incorporate additional among-sample variability due to 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, among-sampler variability was low in dead *Calluna* but the coefficient of variation was higher than expected for such a low among-sampler variability. This is likely attributable to outliers resulting from the misidentification of live *Calluna* as dead. Where dead fuel is correctly identified, this material is considered easy to collect following the sampling protocol and among-sampler variability is low. Among-sampler variability in this case is mainly a concern where brown *Calluna* is incorrectly identified as dead. Where dead fuel moisture is the most important variable, among-sampler variability may be less important to account for than time-of-day and illogical values from mis-identifications can be filtered out of the dataset.

There may also be variability within individual samplers through time. For instance, sampler accuracy may increase with experience gained or decrease due to fatigue as the day goes on. These changes may be intertwined with diurnal fluctuations in fuel moisture variability, as was the case in this study, and so are unable to be disentangled. However, temporal changes in individual sampler variability should be considered during sampling campaign design to minimise this influence (e.g. allow time for instructions, practice, and feedback before beginning and consider the required length of sampling campaigns to manage fatigue and comfort of samplers).

Considering among-sampler variability in survey design

Carefully considered sampling protocols can minimise sources of among-sampler variability prior to field collection (Dickinson *et al.* 2010; Morrison 2016). We aimed to reduce sampling effort variability by having a clear protocol for where, when, and how samples should be collected. We also controlled for among-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. Where sources of variability cannot be minimised through sampling protocols, statistical tools can sometimes be used to account for among-sampler variability 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 and Hochachka 2012) have been used in citizen science ecological studies to account for this variability. However, statistical tools can only be utilised when it is possible to isolate sampler identity from other covariates. Where sampler identity is not known or is confounded with other variables such as geographic location or time, the underlying controls on fuel moisture variability cannot be disentangled.

Larger fuel moisture sampling campaigns that aim to quantify the spatio-temporal variability in fuel moisture content will likely 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)) could also be collected to further quantify among-sampler variability (Kelling *et al.* 2015). Fuel moisture samples should have a sampler identifier to relate metadata metrics to fuel moisture content. Sampler metadata 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 variability (August *et al.* 2020).

Implications

Among-sampler variability 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 among-sampler variability that will be more accurate than a single value. Accounting for among-sampler variability opens opportunities to maximise the potential of citizen science research to characterise fuels and understand regional fuel dynamics beyond the capability of most traditional field experiments. For instance, capturing fuel load and fuel flammability are also essential to develop fuel models that are representative of the range of regional ecosystems they are being developed for. Fuel height and fuel samples could be collected by citizen scientists for research developing wider aspects of fuel and fire behaviour models. Furthermore, community hubs of citizen scientists could implement long-term fuel moisture monitoring campaigns to assess local wildfire danger, thereby creating wildfire-aware community networks within rural–urban interfaces and promoting risk reduction strategies.

Supplementary material

Supplementary material is available online.

References

Aagaard K, Lyons JE, Thogmartin WE (2018) Accounting for Surveyor Effort in Large-Scale Monitoring Programs. *Journal of Fish and Wildlife Management* **9**, 459–466. doi:10.3996/022018-JFWM-012

Arazy O, Malkinson D (2021) A Framework of Observer-Based Biases in Citizen Science Biodiversity Monitoring: Semi-Structuring Unstructured Biodiversity Monitoring Protocols. *Frontiers in Ecology and Evolution* **9**, 693602. doi:10.3389/fevo.2021.693602

August T, Fox R, Roy DB, Pocock MJO (2020) Data-derived metrics describing the behaviour of field-based citizen scientists provide insights for project design and modelling bias. *Scientific Reports* **10**, 11009. doi:10.1038/s41598-020-67658-3

Bartoń K (2022) MuMIn: Multi-Model Inference. https://CRAN.R-project.org/package=MuMIn.

Bates D, Mächler M, Bolker B, Walker S (2015) Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software* **67**, 1–48. doi:10.18637/jss.v067.i01

Bilgili E, Coskuner KA, Usta Y, Saglam B, Kucuk O, Berber T, Goltas M (2019) Diurnal surface fuel moisture prediction model for Calabrian pine stands in Turkey. *IForest* **12**, 262–271. doi:10.3832/ifor2870-012

Bird TJ, Bates AE, Lefcheck JS, Hill NA, Thomson RJ, Edgar GJ, Stuart-Smith RD, Wotherspoon S, Krkosek M, Stuart-Smith JF, Pecl GT, Barrett N, Frusher S (2014) Statistical solutions for error and bias in global citizen science datasets. *Biological Conservation* **173**, 144–154. doi:10.1016/j.biocon.2013.07.037

Brown TP, Hoylman ZH, Conrad E, Holden Z, Jencso K, Jolly WM (2022) Decoupling between soil moisture and biomass drives seasonal variations in live fuel moisture across co-occurring plant functional types. *Fire Ecology* **18**, 14. doi:10.1186/s42408-022-00136-5

Cawson JG, Nyman P, Schunk C, Sheridan GJ, Duff TJ, Gibos K, Bovill WD, Conedera M, Pezzatti GB, Menzel A (2020) Estimation of surface dead fine fuel moisture using automated fuel moisture sticks across a range of forests worldwide. *International Journal of Wildland Fire,* **29**, 548–559. doi:10.1071/WF19061

Cox TE, Philippoff J, Baumgartner E, Smith CM (2012) Expert variability provides perspective on the strengths and weaknesses of citizen-driven intertidal monitoring program. *Ecological Applications* **22**, 1201–1212. doi:10.1890/11-1614.1

Davies GM, Legg CJ, O'Hara R, MacDonald AJ, Smith AA (2010) Winter desiccation and rapid changes in the live fuel moisture content of Calluna vulgaris. *Plant Ecology & Diversity* **3**, 289–299. doi:10.1080/17550874.2010.544335

Devictor V, Whittaker RJ, Beltrame C (2010) Beyond scarcity: citizen science programmes as useful tools for conservation biogeography. *Diversity and Distributions* **16**, 354–362. doi:10.1111/j.1472-4642.2009.00615.x

Dickinson JL, Zuckerberg B, Bonter DN (2010) Citizen Science as an Ecological Research Tool: Challenges and Benefits. *Annual Review of Ecology, Evolution, and Systematics* **41**, 149–172. doi:10.1146/annurev-ecolsys-102209-144636

Dickman LT, Jonko AK, Linn RR, Altintas I, Atchley AL, Bär A, Collins AD, Dupuy J-L, Gallagher MR, Hiers JK, Hoffman CM, Hood SM, Hurteau MD, Jolly WM, Josephson A, Loudermilk EL, Ma W, Michaletz ST, Nolan RH, O'Brien JJ, Parsons RA, Partelli-Feltrin R, Pimont F, Resco de Dios V, Restaino J, Robbins ZJ, Sartor KA, Schultz-Fellenz E, Serbin SP, Sevanto S, Shuman JK, Sieg CH, Skowronski NS, Weise DR, Wright M, Xu C, Yebra M, Younes N (2023) Integrating plant physiology into simulation of fire behavior and effects. *New Phytologist* **238**, 952–970. doi:10.1111/nph.18770

Ellis TM, Bowman DMJS, Jain P, Flannigan MD, Williamson GJ (2022) Global increase in wildfire risk due to climate-driven declines in fuel moisture. *Global Change Biology* **28**, 1544–1559. doi:10.1111/gcb.16006

Farewell TS, Truckell IG, Keay CA, Hallett SH (2011) The derivation and application of Soilscapes: soil and environmental datasets from the National Soil Resources Institute, Cranfield University. Available at https://www.cranfield.ac.uk/themes/environment-and-agrifood/landis/soilscapes#

Fink D, Hochachka WM (2012) Citizen Science. In 'Public Participation in Environmental Research'. (Eds JL Dickinson, R Bonney) pp. 125–138. (Cornell University Press) doi:10.7591/9780801463952-015

Glaves DJ, Crowle AJ, Bruemmer C, Lenaghan SA (2020) 'The causes and prevention of wildfire on heathlands and peatlands in England (NEER014).' (Natural England: Peterborough)

Isaac NJB, van Strien AJ, August TA, de Zeeuw MP, Roy DB (2014) Statistics for citizen science: extracting signals of change from noisy ecological data. *Methods in Ecology and Evolution* **5**, 1052–1060. doi:10.1111/2041-210X.12254

Kelling S, Fink D, La Sorte FA, Johnston A, Bruns NE, Hochachka WM (2015) Taking a 'Big Data' approach to data quality in a citizen science project. *Ambio* **44**, 601–611. doi:10.1007/s13280-015-0710-4

Lai G, Quan X, Yebra M, He B (2022) Model-driven estimation of closed and open shrublands live fuel moisture content. *GIScience & Remote Sensing* **59**, 1837–1856. doi:10.1080/15481603.2022.2139404

Matthews S (2014) Dead fuel moisture research: 1991-2012. *International Journal of Wildland Fire* **23**, 78–92. doi:10.1071/WF13005

Matthews S, Gould J, McCaw L (2010) Simple models for predicting dead fuel moisture in eucalyptus forests. *International Journal of Wildland Fire* **19**, 459–467. doi:10.1071/WF09005

Miller L, Zhu L, Yebra M, Rüdiger C, Webb GI (2022) Multi-modal temporal CNNs for live fuel moisture content estimation. *Environmental Modelling & Software* **156**, 105467. doi:10.1016/j.envsoft.2022.105467

Morrison LW (2016) Observer error in vegetation surveys: a review. *Journal of Plant Ecology* **9**, 367–379. doi:10.1093/jpe/rtv077

Nakagawa S, Schielzeth H (2013) A general and simple method for obtaining R^2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution* **4**, 133–142. doi:10.1111/j.2041-210x.2012.00261.x

Nolan RH, Foster B, Griebel A, Choat B, Medlyn BE, Yebra M, Younes N, Boer MM (2022*a*) Drought-related leaf functional traits control spatial and temporal dynamics of live fuel moisture content. *Agricultural and Forest Meteorology* **319**, 108941. doi:10.1016/j.agrformet.2022.108941

Nolan V, Gilbert F, Reader T (2022*b*) Solving sampling bias problems in presence–absence or presence-only species data using zero-inflated models. *Journal of Biogeography* **49**, 215–232. doi:10.1111/jbi.14268

Norum RA, Miller M (1984) Measuring fuel moisture content in Alaska: standard methods and procedures. General Technical Report PNW-171. U.S. (Department of Agriculture, Forest Service, Pacific Northwest Forest and Range Experiment Station) https://doi.org/10.2737/PNW-GTR-171

Nyman P, Baillie CC, Duff TJ, Sheridan GJ (2018) Eco-hydrological controls on microclimate and surface fuel evaporation in complex terrain. *Agricultural and Forest Meteorology* **252**, 49–61. doi:10.1016/j.agrformet.2017.12.255

Pivovaroff AL, Emery N, Sharifi MR, Witter M, Keeley JE, Rundel PW (2019) The Effect of Ecophysiological Traits on Live Fuel Moisture Content. *Fire* **2**, 28. doi:10.3390/fire2020028

R Core Team (2022) 'R: A Language and Environment for Statistical Computing.' (R Foundation for Statistical Computing: Vienna, Austria) Available at https://www.R-project.org/

Scarff FR, Lenz T, Richards AE, Zanne AE, Wright IJ, Westoby M (2021) Effects of plant hydraulic traits on the flammability of live fine canopy fuels. *Functional Ecology* **35**, 835–846. doi:10.1111/1365-2435.13771

Sicacha-Parada J, Steinsland I, Cretois B, Borgelt J (2021) Accounting for spatial varying sampling effort due to accessibility in Citizen Science data: A case study of moose in Norway. *Spatial Statistics* **42**, 100446. doi:10.1016/j.spasta.2020.100446

Slijepcevic A, Anderson WR, Matthews S (2013) Testing existing models for predicting hourly variation in fine fuel moisture in eucalypt forests. *Forest Ecology and Management* **306**, 202–215. doi:10.1016/j.foreco.2013.06.033

Zhang Y, Sun P (2020) Study on the diurnal dynamic changes and prediction models of the moisture contents of two litters. *Forests* **11**, 95. doi:10.3390/f11010095

Data availability. The data and code that support this study are available in FigShare at https://doi.org/10.6084/m9.figshare.22683508 and https://doi.org/10.6084/m9.figshare.22683352.v1, respectively.

Conflicts of interest. The authors declare no conflicts of interest.

Declaration of funding. This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 860787 (PyroLife Innovative Training Network) and the NERC Highlight project NE/T003553/1. LJG was supported by NERC grant NE/T009373/1.

Acknowledgements. We thank the two anonymous reviewers who provided valuable feedback that greatly improved the quality of this manuscript. We also thank the 2022 University of Birmingham Geography sub-cohort from module 36261: LC Fieldwork Project Design and GIS for their involvement in this field campaign and Luke Everett for field work support.

Author affiliations

[A]School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham, UK.

[B]Biodiversity, Ecology and Conservation Group, International Institute for Applied Systems Analysis, Vienna, Austria.