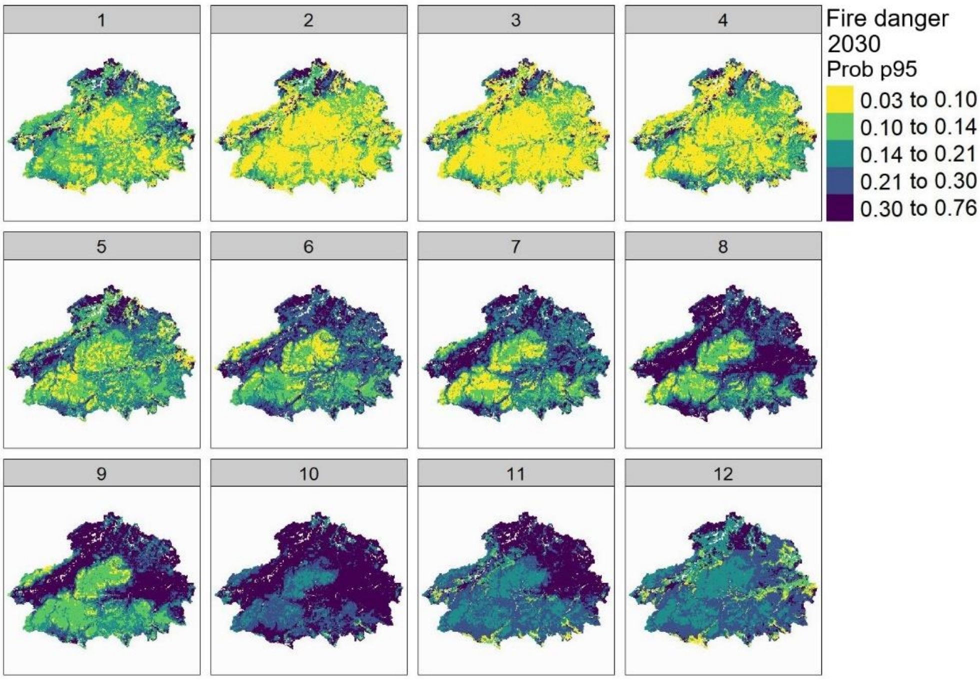
Development of a modelling approach for conducting spatial assessments of future wildfire danger in Scotland

Deliverable 2.4b for the

Project D5-2 Climate Change Impacts on Natural Capital



April 2025

Summary

This report is a product of the Scottish Government Strategic Research Programme project JHI-D5-2 'Climate Change Impacts on Natural Capital'. This is report for Deliverable 2.4b: 'Development of spatial assessments of wildland fire risk and impacts on NC assets'.

The purpose of this report is to present the results of spatial assessments of future fire danger in the Cairngorms National Park for the 2020 -2049 period, generated using a probabilistic fire danger model trained using historical fire data for different fuels and data layers of climatic projections. The aim of this report is to present the methods and data layers used to develop and validate the fire danger model and present and discuss the generated spatial assessment of fire danger within the Park. The report also provides a discussion on limitations of this modelling approach along with potential improvements and suggestions for next steps towards developing fire risk assessment frameworks.

Model development follows the approach of the Risk and Opportunities Assessment Framework (ROAF) being developed in this project, where a Natural Capital (NC) asset's risk is defined as a function of its Vulnerability and Exposure to a Threat (R=VET). This report also provides the basis for planned work for Deliverable D2.5a: 'Estimate impacts on assets (condition, functions)' (due December 2026).

The need for increased capabilities to understand fire danger and risks has been highlighted following publication of other reports from the JHI-D5-2 'Climate Change Impacts on Natural Capital'. These show how much Scotland's climate has already changed and what the future climatic conditions influencing fire danger and risk may be:

- Climate Trends and Future Projections in Scotland
- Climate Extremes in Scotland
- Assessment of Natural Capital exposure to current and future meteorological drought
- Fire danger assessment of Scottish habitat types

Advances in Technical Capabilities

This report has been developed through technical advances made in the JHI-D5-2 project related to new analytical capability for calculating and mapping fire weather indices using time series of future climatic variables, development of a Machine Learning model with the capacity for simulating fire occurrence probabilities and conducting spatial fire danger assessments, and generation of R scripts for visualisation and plotting of the simulation results.

Contents

Citation:

This report should be cited as:

Gagkas Z., Jabloun, M., Glendell, M., Rivington, M., (2025). Development of a modelling approach for conducting spatial assessments of future wildfire danger in Scotland. Deliverable 2.4b for the Project D5-2: Climate Change Impacts on Natural Capital. The James Hutton Institute, Aberdeen. Scotland. DOI

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Acknowledgements

This report has been produced by the D5-2 Climate Change Impacts on Natural Capital Project funded by the Scottish Government Rural and Environment Science and Analytical Services Strategic Research Programme (2022-2027).

Introduction

This work aimed to develop a spatial Machine Learning (ML) model with the capacity for simulations of fire occurrence probability using climatic variable inputs, including data layers of future climatic projections, with the specific objective of using model simulations to conduct spatial assessments of fire danger. Previously (Glendel et al., 2024) we proposed using a modelling approach based on Bayesian Belief Network (BNNs). However, initial analysis showed that this was not feasible due to knowledge gaps related to appropriate fire weather thresholds for establishing danger classes that made it difficult to propagate the probability tables required in the BBN approach. Therefore, we decided to develop an alternative spatial modelling approach using an ML algorithm (Random Forest) that is known to perform well in detecting complex and non-linear relationships between explanatory variables of fire danger. This allowed us to build on experience from the application of this algorithm to probabilistic soil mapping and leverage the available empirical data from past fire occurrence at high temporal resolution. Meanwhile, the strength of the Bayesian Network lies in integrating both biophysical and socio-economic variables and this will remain an option in future research. Here we used the Random Forest approach to simulate the fire danger component. In future research, the Bayesian Network approach could help to integrate these results to simulate fire risk, including fire risk perception, vulnerability and resilience assessment, impacts on ecosystem services provision and monetary costs.

The focus of this work was on large scale wildfire danger assessments for seminatural habitats where most of the more remote and destructive fires typically occur in Scotland. Fires on cultivated land or in the wildland-urban interface were outside the scope of this study. The fire danger model was trained using fire/burnt area data at the national scale, but we used the Cairngorms National Park for model deployment and for producing fire danger assessments for selected future climate projections. The Park was selected because it is quite extensive and supports climatic, habitat and landscape characteristics that are representative of Scotland as a whole. Compared to attempting a national deployment, this approach enabled us to better assess the model's performance and identify weaknesses or limitations of this approach, and helped with identifying drivers of fire danger predictions and their relative importance.

Methods for model development

Overview

We have previously explored frameworks for fire danger and risk assessment (Gagkas et al., 2023), and we have adopted the approach by Chuvieco et al. (2023) in which Fire Danger is the function of the likelihood of fire propagation and the presence of an ignition source (Figure 1). This approach forms the basis of model's conceptual structure on which:

- Climatic parameters (based on emission scenarios) for observed and future climate are used to calculate fire weather indices, including the effect of seasonality, that are used to assess fuel moisture of selected Natural Capital (NC) assets and assess the likelihood of fire propagation. In this study the focus is on wildfires burning seminatural vegetation so the selected NC assets are Broadleaves, Conifers, Seminatural grasslands (mainly Acid grasslands), Heather (Shrublands), Bogs (Peatlands) and Montane vegetation (e.g. scrub).
- Accessibility is used as a proxy for assessing the likelihood of the presence of an ignition source.
- Likelihoods of propagation and ignition are combined to provide an assessment of Fire Danger.

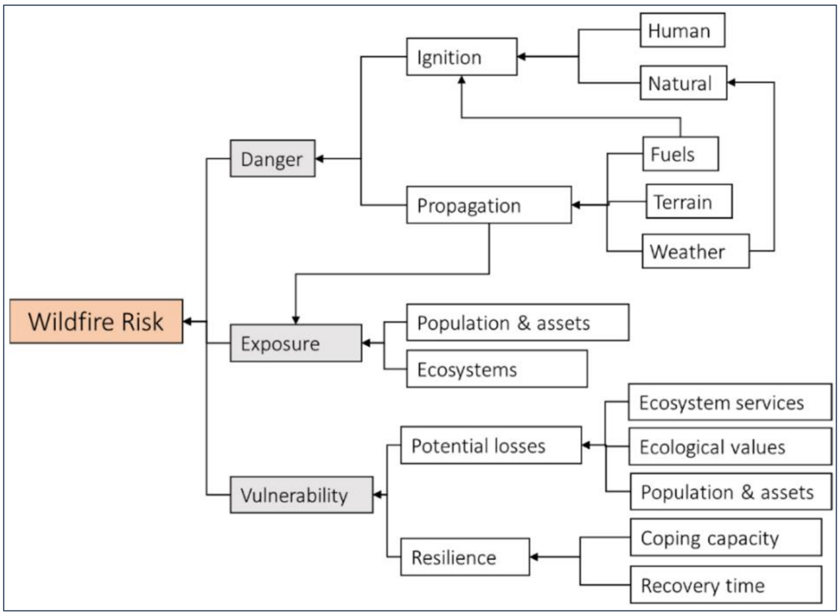


Figure 1. Framework for Wildfire Risk Assessments proposed by Chuvieco et al. (2023).

We used the Cairngorms National Park (CNP) as our study area for trial and testing the fire danger model and conducting spatial fire danger assessments for the selected fuel types. Overall, the methodology for developing the modelling approach comprises three (3) main components:

a) Develop the training dataset by randomly sampling spatial data layers of burnt area polygons and extracting values of selected covariates (predictors) at the locations of the generated virtual samples.
b) Train and fine-tune the ML model using the training dataset and assess model performance.
c) Use the ML model to simulate fire occurrence probabilities within the CNP and conduct spatial assessments to identify hotspots of future fire danger.

A further objective of this work was also to "unlock the black box" to explore the patterns identified by the ML algorithm for the covariates used, both for checking that these patterns are conceptually sound but also for purposes of knowledge discovery.

Modelling approach

Studies modelling wildfire ignition risk and wildfire danger have previously utilised a logistic regression approach (e.g., Catry et al., 2009; Dixon and Chandler, 2019). However, ensemble decision trees, such as Random Forests (RF) (Breiman, 2001), are a robust alternative method to logistic regression for modelling non-linear relationships for both regression and classification purposes (Kirasich et al., 2018), and for this reason, the use of RF in wildfire modelling has seen a steady increase in the last few years (Malik et al., 2021; Tong and Gernay, 2023). RF is a ML algorithm with many advantages for complex modelling, such as interpretability, its ability to deal with missing data and with autocorrelated variables, and to utilise both discrete (i.e., categorical) and numeric (continuous) predictors. RF uses an ensemble of decision trees constructed by randomly selecting a group of observations from the training dataset (bootstrapping) and splits at each tree node are made by using the best predictor of a randomly selected subset from the entire suite of input variables (Breiman, 2001). RF uses decision trees to produce error prediction using an out-of-bag (OOB) strategy. OOB constructs each tree using bootstrap samples with replacement so that, on average, two-thirds of the observations are being used for training. The remaining observations are left out to test model error (i.e., the OOB error). RF changes the order of arrangement (permutation) of the covariates randomly and considers all possibilities to select covariates in the OOB samples. This approach is considered to make RF less susceptible to overfitting (Liaw and Wiener, 2002).

In this study we used random forest probability machines (RFPMs), which are an implementation of RF and are consistent nonparametric regression machines applied to binary or categorical outcomes that have been designed to estimate conditional probabilities rather than predict an expected response (Malley et al., 2012). In RFPMs, each tree provides a conditional probability estimate which is obtained by taking the proportion of observations in the training data set with an outcome value of 1 in the residing node. The final probability estimate is obtained by taking an average of all the individual tree estimates in the forest. In the context of predictive modelling, wildfire (ignition) and non-ignition samples are treated as the dependent variable, while the information extracted from a number of explanatory variables at sample point locations is used as the model predictors. The result of this modelling exercise is a matrix of probabilities of fire occurrence (ranging from 0 to 1) that can be classified into danger classes to produce fire danger class maps. An additional important output of the modelling are metrics of relative importance of the different explanatory variables used as predictors of fire danger, which can be used to identify drivers of probable fire danger in a given area.

Development of the training dataset

Generation of sample points

The selected modelling approach requires both ignition (wildfire locations) and non-ignition sample points. Fire/ignition locations in Scotland are recorded by the Scottish Fire and Rescue Service (SFRS), but previous research has found low positional accuracy of recorded fires and difficulty in identifying fire incidents that related to wildfires (Gagkas et al., 2021). In the absence of an alternative dataset of fire ignitions with national coverage, wildfire locations were determined using 169 polygons of burnt areas in ESRI shapefile (vector) format for the 2011-2019 period, of which 151 were provided by the European Forest Fire Information System (EFFIS) and the remaining 18 have been previously mapped by Gagkas et al. (2021). All selected fires had burnt almost exclusively seminatural vegetation. Although access was available to more recent EFFIS wildfire data, the time period was not extended post 2019 because burnt areas had to temporally coincide with the daily time-series of observed climate that were used to calculate climatic variables and fire weather indices for the respective fire dates (see Section: Covariates). Moreover, older (pre-2019) burnt area mapping by EFFIS detected mostly larger (>30 ha) fires because it was based on the semi-automatic classification of NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery using ancillary spatial datasets, but more recently, due to inclusion of high-resolution Sentinel 2 imagery, smaller fires can also be detected that can be attributed to managed burning (Gagkas et al., 2023). Because this work focused only on wildfires, we used only the pre-2019 burnt areas to ensure that prescribed burning was excluded from the analysis. To further ensure this, we removed burnt areas less than 5 ha in size that could be attributed to managed burning. Also, no fires were selected that had occurred in Shetland because this area is not covered by the observed climate dataset. Burnt area polygons contained information about the location of the fire, the respective administrative unit (i.e., Local Authority), initial and final fire dates and the size of the burnt area. In terms of temporal coverage, there were no burnt areas identified that occurred in August, September and November, whilst most historical fires had occurred in April.

Climate data used to determine baseline climate and fire weather during fire initiation and for simulating future fire danger are available at 1 km grid squares. To ensure that climatic and fire weather conditions at the time of burning were represented in the training dataset, each burnt area polygon was divided to segments based on the overlapping 1 km climate grid squares, and one random sample point was drawn within each burnt area segment using QGIS version 3.40 (QGIS.org, 2025) (Figure 2). This process resulted in 1,214 virtual fire/ignition sample points (Figure 3). An equal number of non-ignition sample points was randomly drawn (Figure 3) a) outside the areas of the burnt areas polygons, extended by a 1 km buffer to ensure that ignition and non-ignition points did not fall within the same 1 km climate grid square for a given fire date, and b) within areas covered by seminatural vegetation, as mapped by the land cover dataset used (described below in Section: Covariates). Non-ignition sample points were also weighted by fire date, specified as the date of fire initiation, i.e., the same number of ignition and non-ignition sample points was randomly drawn for a given fire date, to ensure a temporally balanced representation of climatic and fire weather conditions within both burnt and burnt areas.

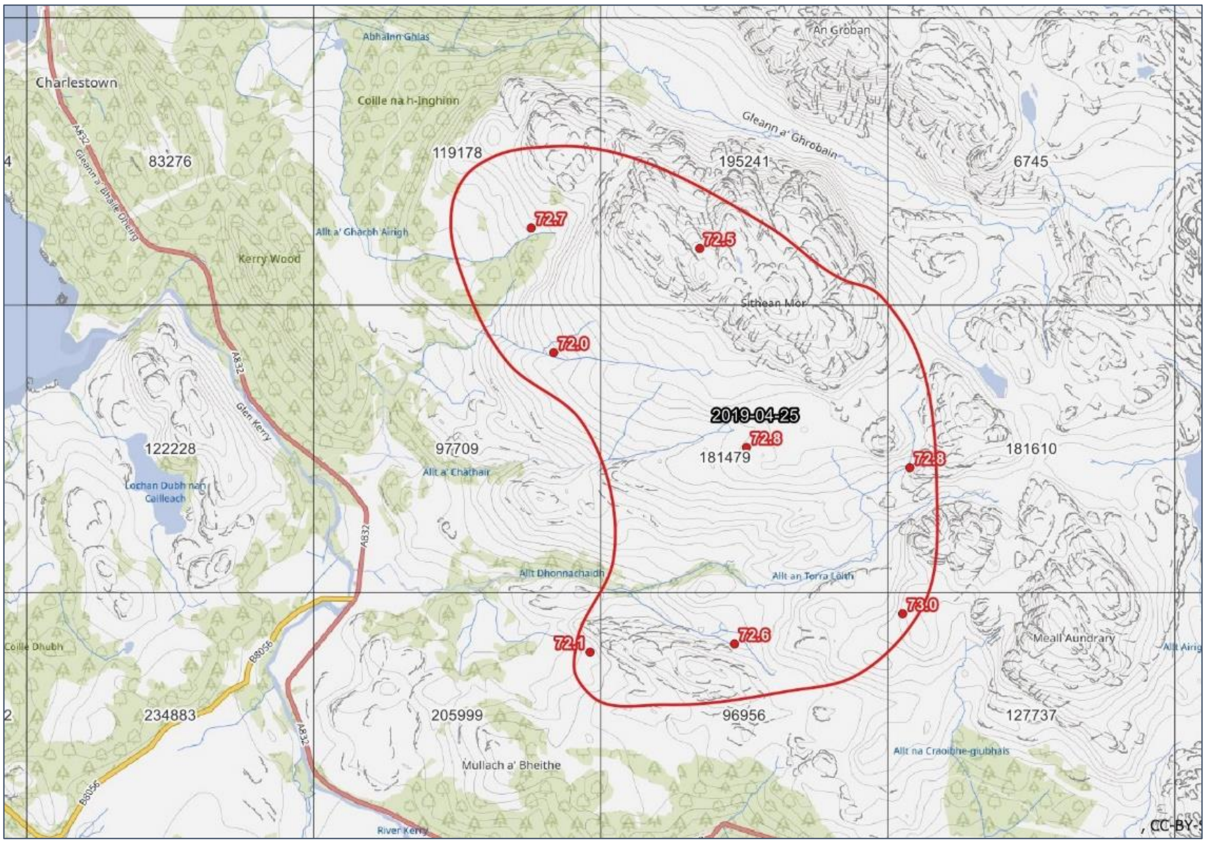


Figure 2. Example of random sampling of ignition points within a burnt area and for segments defined based on 1 km climate grid squares, with their respective IDs given as labels. Labels (in red) of sample points give the calculated value of Fine Fuel Moisture Code (FFMC) for the given fire date (April 25th 2019). © Crown copyright and database right (2025). All rights reserved. The James Hutton Institute, Ordnance Survey Licence Number AC0000812928.

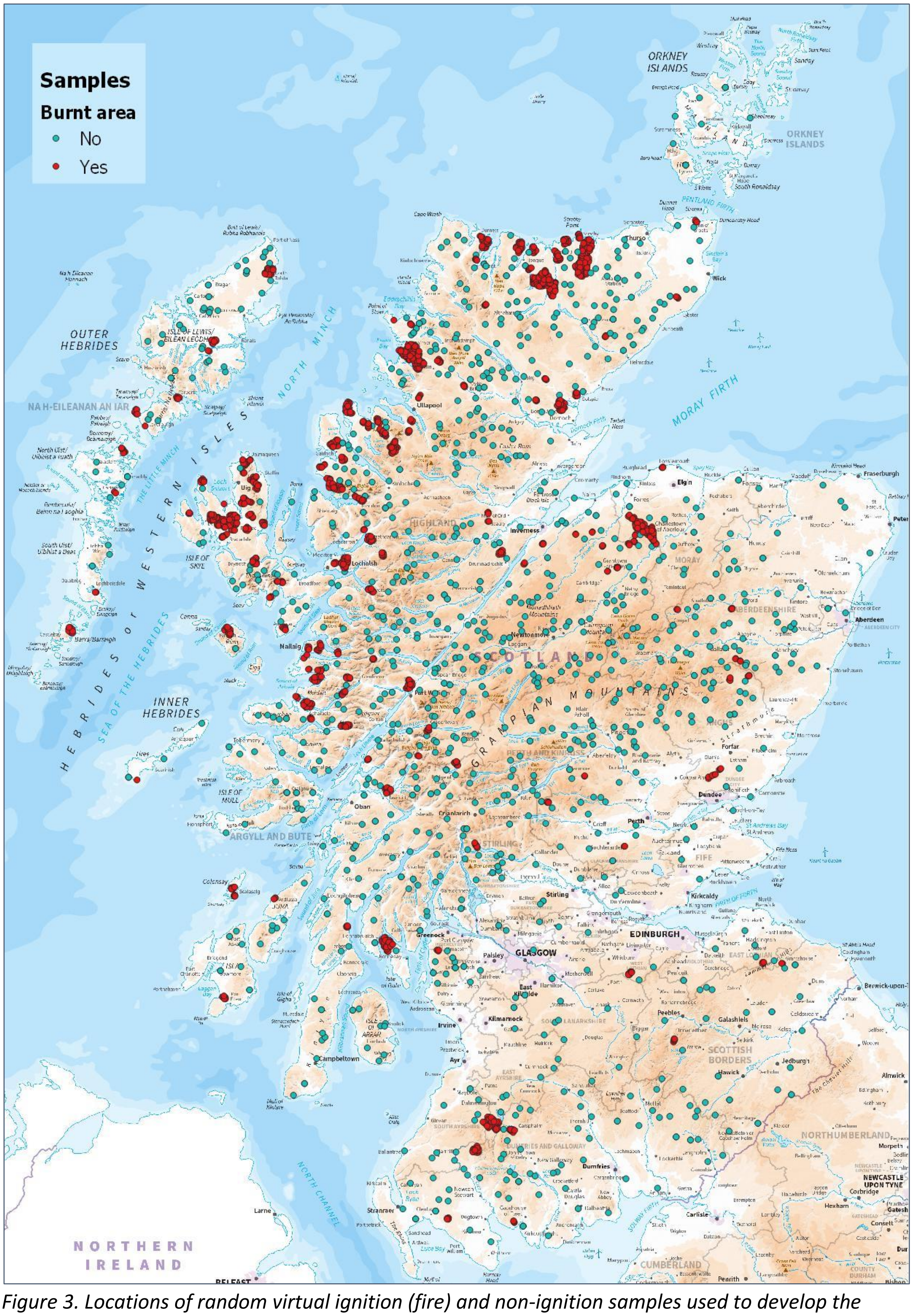


Figure 3. Locations of random virtual ignition (fire) and non-ignition samples used to develop the training dataset. © Crown copyright and database right (2025). All rights reserved. The James Hutton Institute, Ordnance Survey Licence Number AC0000812928.

Covariates

We developed an initial set of 18 covariates that relate to wildfire propagation and ignition, these are described below and summarised in Table 2. The training set was generated by extracting all covariate values at the locations of the ignition and non-ignition samples.

Baseline climate and fire weather

Baseline climate and fire weather for the selected burnt areas in Scotland was determined using observed, daily meteorological variables at 1 km resolution for the selected fire dates from the Climate hydrology and ecology research support system (CHESS-Met dataset), available from 1961-2019 over Great Britain (Robinson et al., 2023). Of the available meteorological variables, we used daily temperature, and precipitation totals to check how important these more accessible data layers were for the model's performance. Fire weather was determined using the fire weather indices of the Canadian Fire Weather Index System (CFWIS) (Figure 4), a detailed description of which is given in Taylor et al. (2021). In the absence of fire weather codes specific to Scottish climatic and vegetation conditions, CFWIS-based fire weather is used in the model as a proxy of the moisture of different fuel fraction types and of fire behaviour (Table 1) and hence of climatically-driven fire danger. For comparison, in heather dominated moorlands, Taylor et al. (2021) suggest that possible Scottish vegetation equivalents for the Fine Fuel Moisture Code (FFMC) are the litter, moss and fibrous organic material down to amorphous organic material, and for the Drought Code (DC) the amorphous organic layer with highly variable depth (from centimetres to metres in deep peats), while for the Duff Moisture Code (DMC) is the loosely compacted organo-mineral or organic topsoil, similar to the original CFWIS. Each moisture code (FFMC, DMC and DC) has a time lag and rainfall threshold: 0.667, 15 and 53 days and 0.6, 1.5 and 2.8 mm of rain for FFMC, DMC and DC, respectively. If rainfall is lower than the threshold value, the code value does not decrease (Taylor et al., 2021). Higher moisture code (FFMC, DMC, DC) values indicate respective drier fuel layers, higher Initial Spread Index (ISI) values indicate windier conditions, while higher Fire Weather Index (FWI) values indicate higher fire severity.

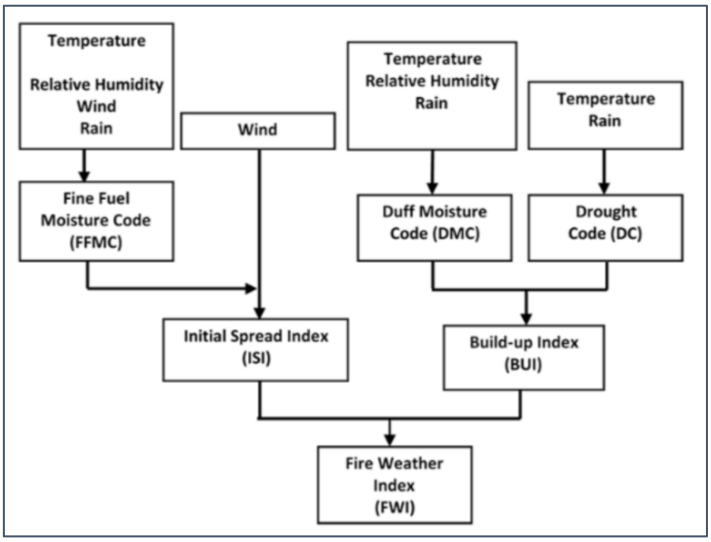


Figure 4. Components of the Canadian Fire Weather Index system (CFWIS) (from Taylor et al., 2021)

Previous work has found that heathland and moorland fire occurrence is not well captured by the FWI and other CFWIS indices in Scotland because fuel models within the CWFIS do not match the fuel structure of heather moorland (Davies and Legg, 2016; Taylor et al., 2021). However, a positive relationship has been found between the combined use of the FFMC and Initial Spread Index (ISI) indices and fire occurrence in Scotland, UK, and Northern Europe for winter-spring fires in heather moorland (Davies and Legg, 2016), while CFWIS has been found to work relatively well for capturing the occurrence of late spring and summer forest fires in Scotland (Taylor et al, 2021). Hence, in this study we chose to explore how the combined use of the fire weather indices can be used in a ML modelling approach for fire danger that can potentially identify non-linear relationships between the various indices.

Table 1. Description of codes of the Canadian Fire Weather Index System

Type	Code/Index	Description
Fuel moisture	Fine Fuel Moisture Code (FFMC)	Moisture content of cured leaves, needles and small dead twigs on the forest floor
	Duff Moisture Code (DMC)	Moisture content of loosely-compacted, partially decomposed needle litter
	Drought Code (DC)	Moisture content of deep layers of compact humus and organic matter
Fire behaviour	Initial Spread Index (ISI)	Combines FFMC and wind speed to provide representation of potential rate of spread without fuel quantity estimate
	Build-up Index (BUI)	Weighted combination of DMC and DC designed to represent total fuel available for combustion
	Fire Weather Index (FWI)	Weighted combination of ISI and BUI designed to provide representation of potential fireline intensity

The fire weather indices were calculated using the daily meteorological variables of each respective fire date (defined as the date of fire initiation) using the cffdrs package in R (Wang et al., 2017) that has been previously installed in the UK Crop Diversity high-performance computing platform[1]. In previous work (Taylor et al., 2021; Gagkas et al., 2023) we extracted CFWIS indices from EFFIS fire danger forecasts at 8km grid resolution; however, in this study we chose to calculate CFWIS indices using CHESS-Met to be consistent with the future fire weather index calculations based on CHESS-SCAPE, both of which are available at a much finer resolution of 1 km x 1 km.

Fuel Types

In previous work (Gagkas et al., 2023) we used the UKCEH Land Cover Map (LCM) for 2020 (Morton et al., 2021) to determine fuel type composition within EFFIS burnt area polygons. However, there is a well-recognised issue with LCM products of interclass confusion when mapping upland, seminatural habitats of low vegetation that usually occur on peaty soils using analysis of satellite imagery, due to their similar spectral signatures (Morton et al., 2021). This means that the distinction between heathlands and peatlands/bogs, where most wildfires occur (Gagkas et al., 2023), may be misleading as it is effectively based on the depth of the organic layer of the soil and because a major fuel type above ground on peat bogs is also shrubs (mainly heather). To overcome this issue, we used the Land Cover Map of Scotland 1988 (LCS88) (MLURI, 1993) that was the first ever national (air-photo) census of land cover in Scotland to describe the principal features and characteristics of the countryside. An important aspect of the classification system is that it allows for mosaics of the land cover types to be identified, where the pattern of cover types was so complex that individual types could not, at the selected interpretation scale, be separated. This approach aligns well with defining the main Scottish fuel types.

[1] https://www.cropdiversity.ac.uk

Obviously, the extent of woodlands and forestry in LCS88 is outdated; hence we used the National Forest Inventory (NFI[2]) Scotland for 2015 (downloaded for Forestry Commission's Open Data portal[3]) to update the LCS88 mapping of woodlands and forests for the time period of the selected burnt areas (2011-2019). For the purpose of this work, the hybrid LCS88-NFI map was classified to the following fuel types: 1) Broadleaves; 2) Conifers; 3) Seminatural grassland; 4) Heather; 5) Bog (peatlands) and 6) Montane (montane vegetation, low scrub and cliffs in LCS88). Figures 5a and 5b show the monthly fuel type composition of the selected burnt areas (by fire count and burnt area, respectively), which highlights that most fires occur on heather and bogs from early to late spring, while Figure 6a gives the spatial distribution of the selected fuels at national scale.

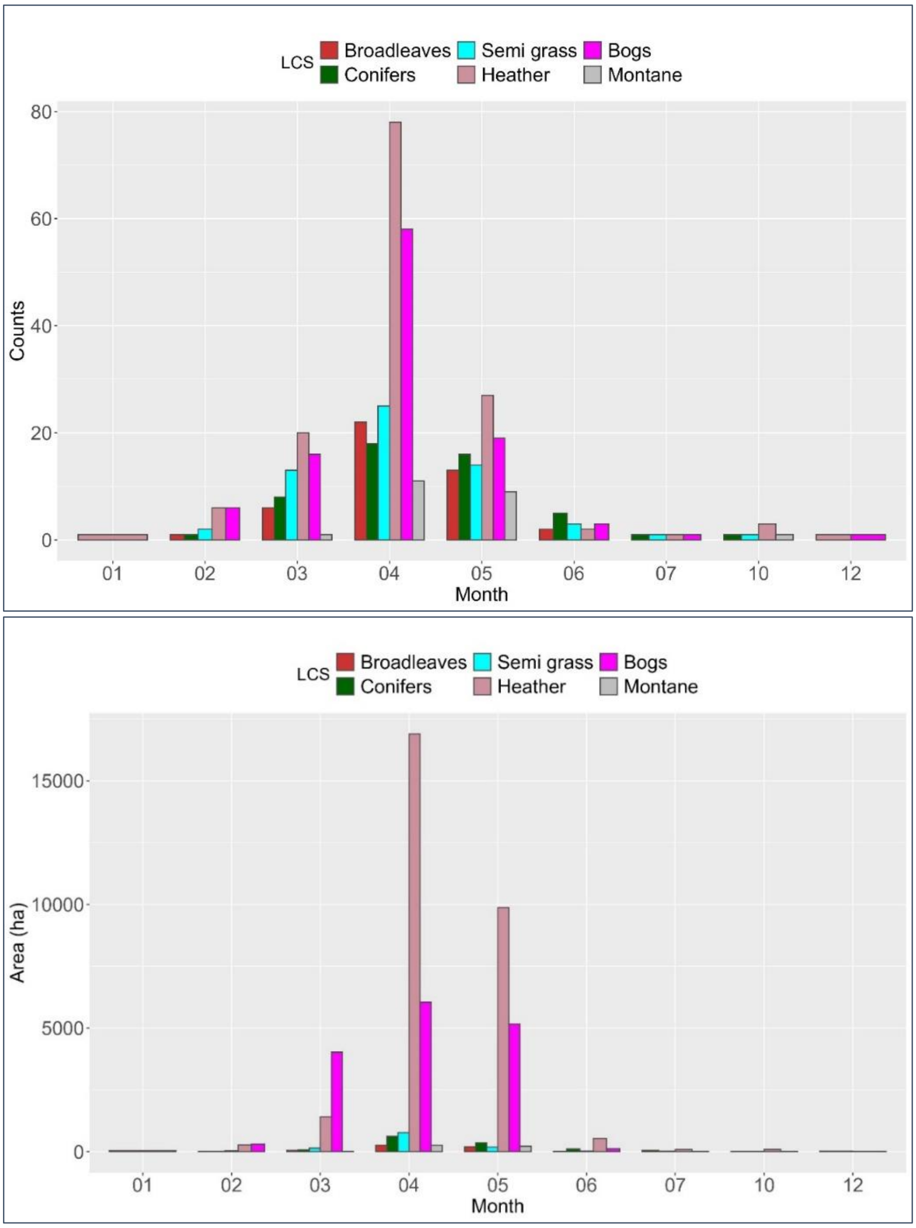


Figure 5. Monthly fuel composition by a) Fire counts and b) Burnt areas (in ha) for the EFFIS burnt area polygons used in this study.

[2] https://www.forestresearch.gov.uk/tools-and-resources/national-forest-inventory/
[3] https://data-forestry.opendata.arcgis.com/

Terrain

Terrain shape and morphology are important for fire ignition due to its influence on wind regimes, solar exposure, rainfall and air temperature and humidity distribution (Chuvieco et al., 2023). The Ordnance Survey (OS) Terrain 50 digital elevation model (DEM) was used to characterise elevation and calculate the following terrain indices in SAGA GIS (Conrad et al., 2015): aspect and slope, wind exposure, diurnal anisotropic heating (DAH) and the SAGA version of topographic wetness index.

Soils

The importance of soils, specifically of soil moisture and wetness for providing resilience to fire propagation and spread, is sometimes overlooked in fire danger studies. For example, fire severity of wildfires in Scotland has been found to be higher in dry heath (found on drier, mineral soils) than wet heath (found on wetter organo-mineral/peaty soils) and blanket bog (found on peat soil) (Naszarkowski et al., 2024). To consider this effect and better help differentiate between fuel types, especially those related to moorland vegetation, we used a digital map of soil series translated to Hydrology of Soil Type (HOST) classes at 50m resolution (Figure 6b) generated from the spatial disaggregation of the National Soil Map 1:250,000 units (Gagkas and Lilly, 2024). HOST classifies soils with similar hydrological behaviour based on information on flow mechanisms, water storage capacity, saturated hydraulic conductivity and geology or parent material (Boorman et al., 1995), and, hence, is considered as an appropriate classification for representing variation in soil water regimes (e.g., dry vs wet soils).

Variables related to ignition sources

Previous research has found that wildfires occurring in very remote and remote rural areas (north and north-western Scotland) affecting mostly heathlands and bogs seemed to be caused mainly by accidental ignitions caused by intentional burns that got out of control, which might be associated with prescribed burning, or by tourism/recreational activities (Gagkas et al., 2021). Accessibility has been found to be directly related to the likelihood of ignition and distances to road or path networks, to parking places and nearest settlements have been found to be the most important predictors of ignition risk in similar studies, e.g., as in the Peak District National Park (Dixon and Chandler, 2019). However, the difference between these approaches and the current study is that they have used known/recorded ignition points to calculate these distance metrics, whilst this study's methodology is agnostic to the location of fire initiation. Nevertheless, we explored the inclusion of distance metrics by calculating distances in QGIS from the location of the virtual ignition and non-ignition sample points to the nearest road and path network (from OS Open Layers) and to nearest rural parking spaces (extracted from OpenStreetMap layers). This resulted in little differentiation in distances between ignition and non-ignition points, and initial model runs showed that the inclusion of these distance metrics did not improve the performance of the model.

Therefore, we used an alternative approach by including the latest version (2022) of the Urban Rural Classification that provides a consistent way of defining urban and rural areas across Scotland and is based upon two main criteria: (i) population as defined by National Records of Scotland (NRS), and (ii) accessibility based on drive time analysis to differentiate between accessible and remote areas in Scotland. The 6-fold classification distinguishes between urban, rural, and remote areas through six categories, while the 8-fold classification used in this study (Figure 6c) further distinguishes between remote and very remote regions.

Regarding the importance of prescribed burning, and muirburn in particular, as an important ignition source in Scottish uplands, there is evidence that muirburn causes a proportion of wildfires that occur on moorland, but there remains uncertainty regarding this proportion (Holland et al., 2022). Recent analysis by Fielding et al. (2024) that used evidence of muirburn quantified using high-resolution imagery (Matthews et al., 2020) and wildfire occurrence determined by aerial and satellite imagery (including EFFIS burnt areas) found limited spatial co-occurrence of wildfire and prescribed burning on moorlands in Scotland, although the authors stressed that it was uncertain whether this was a clear indicator of the proportion of muirburns that might get out of control to become wildfires. Due to these uncertainties, evidence of muirburn, mapped at 1 km grid squares by Matthews et al. (2020) was not used as a covariate in the fire danger modelling; instead we overlaid the future fire danger simulations in the Cairngorms National Park with the mapped muirburn areas to assess their spatial co-occurrence aiming to identify hotspots of high future fire danger where muirburn is also present and which could act as a potential ignition source. It is also worth noting that both elevation and slope influence accessibility and, hence, can be important as a proxy for the presence of ignition sources as well.

Additional variables

Phenology has been found to be a key driver for fire in the UK and comparable humid temperate regions (Nikonovas et al., 2024). The UK's and Scotland's fire regime is characterised by burning in seminatural grasslands and evergreen dwarf shrub ecosystems in early spring when vegetation is still dormant, but during the high-greenness phase in grasslands and heathlands in late spring and summer, fire activity is reduced by a factor of 5 – 6, despite typically elevated fire weather conditions within that period. This shows that seminatural vegetation in UK uplands is very resistant to burning during the high-greenness phase. However, this 'fire barrier' is diminished during severe drought episodes (Nikonovas et al., 2024). Therefore, in order to consider the phenological component in our modelling, we used the recorded fire dates to assign burnt areas three (3) time periods/seasons that are being used by NatureScot[4] in the generation of fire statistics to represent phenological stages of different fuel types: 1) Season T1: January, February, March, April; 2) Season T2: May, June, July, August, September; and 3) Season T3: October, November, December.

We also generated a "Regions" layer (Figure 6d) by aggregating the main river basins in Scotland used in previous modelling work (Gagkas and Lilly, 2019) to create a map of the main five (5) regions of Scotland: North, West, East, Central and South (Figure 6d). This layer was included to provide an additional, spatially explicit context to the modelling approach to assist in identifying patterns related to climatic conditions and land use and soil composition in different areas of Scotland. Also, previous findings indicate that presence and contribution of ignition sources differs between areas and Local Authorities in Scotland (Gagkas et al., 2021).

[4] https://opendata.nature.scot/datasets/scottish-wildfire-and-muirburn-extents

Table 2. Description of collated covariates for developing the training dataset for the fire danger model. Covariates in italics were removed from the final training set (see Section: Final Covariate Selection)

Code	Description	Type	Source	Reference
TEMP	Daily temperature (°C) at fire date	Continuous	CHESS-Met variables at 1km grid square	Robinson et al. (2021a)
PREC	Precipitation total (mm) at fire date	Continuous		
FFMC	Fine Fuel Moisture Code	Continuous		
ISI	Initial Spread Index	Continuous		
DMC	Duff Moisture Code	Continuous		
DC	Drought Code	Continuous		
BUI	*Built-up Index*	*Continuous*		
FWI	Fire Weather Index	Continuous		
Elev	Elevation above sea level in metres	Continuous	Ordnance Survey digital elevation model at 50m grid resolution (OS DTM 50)	OS Open Data
Asp	*Aspect (radians)*	*Continuous*		Zevenbergen and Thorne (1987)
Slope	Slope (radians)	Continuous		
WindExp	*Wind exposure*	*Continuous*		Boehner and Antonic (2009)
DAH	*Diurnal anisotropic heat*	*Continuous*		
SAGA WI	*SAGA Wetness Index*	*Continuous*		
LCS	Land Cover of Scotland 1988 & Forest Inventory	Categorical	Macaulay Land Use Research Institute (MLURI) & Forest Research	MLURI (1993)
HOST	Hydrology of Soil Types classification	Categorical		Boorman et al. (1995)
Season	Assigned based on day of fire initiation	Categorical	EFFIS Burnt Areas	-
UR8	Scottish Government Urban Rural Classification (2022)	Categorical	https://spatialdata.gov.scot	OGL
Regions	Aggregated river basins	Categorical	-	Gagkas and Lilly (2019)

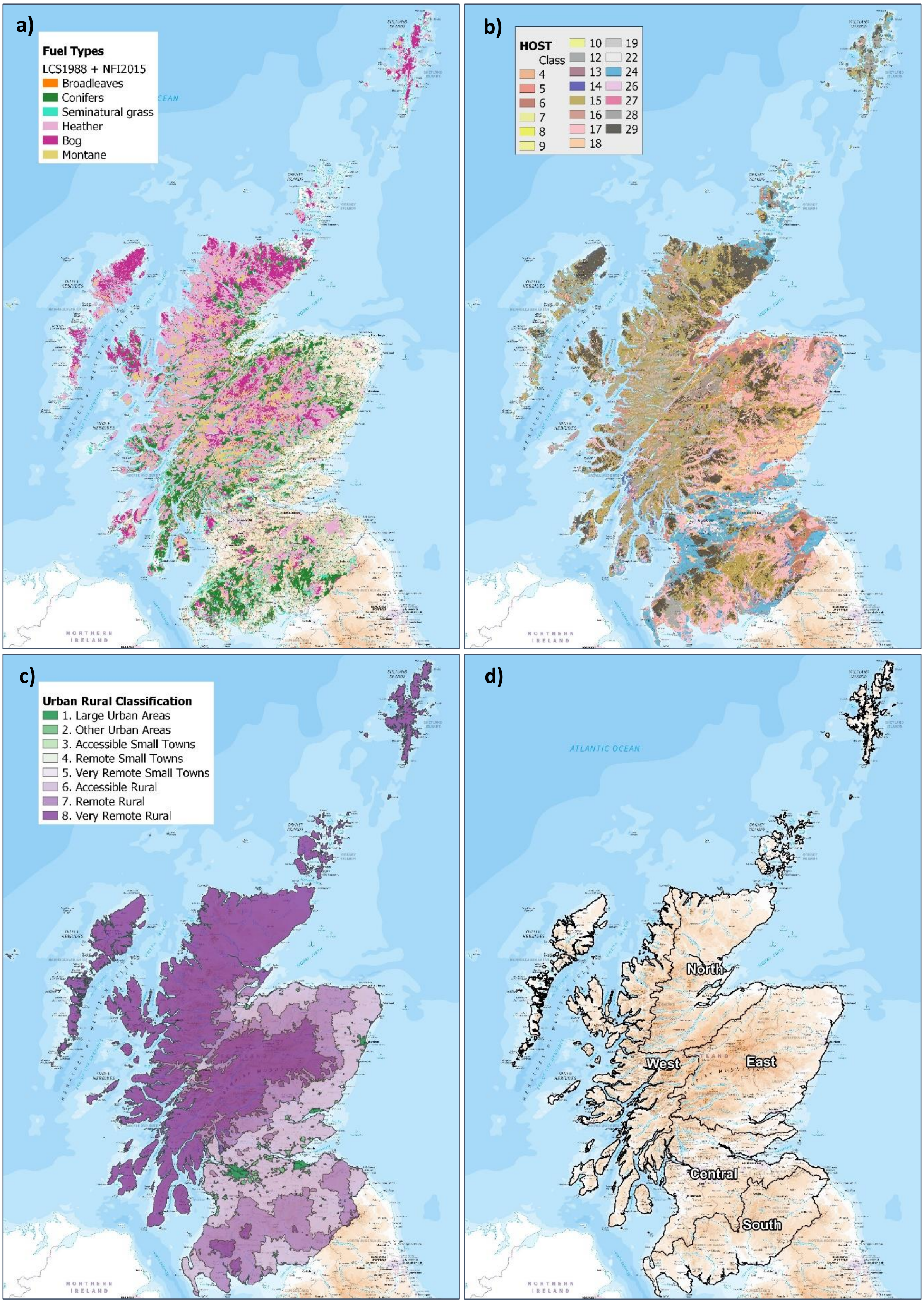


Figure 6. Map of selected categorical covariates a) Fuel type, hybrid map of LCS88 and NFI2015; b) Hydrology of Soil Types (HOST) classes; c) Urban-Rural Classification (8-fold version) and d) Regions. See text for description of covariate generation. © Crown copyright and database right (2025). All rights reserved. The James Hutton Institute, Ordnance Survey Licence Number AC0000812928.

Development of the fire danger model

Final covariate selection

We used a variable selection approach to identify a parsimonious set of key variables (covariates) for simulating fire occurrence probabilities to improve computational efficiency by excluding less-informative predictors, but also because variable selection has also been found to result in small improvements to the accuracy of RF predictions (Gagkas and Lilly, 2019). Initially, we checked autocorrelation between selected covariates in the training dataset using both ignition and non-ignition samples and removed the Built-up Index (BUI) because its values had >0.8 correlation with the Duff Moisture Code (DMC), the latter being one of the main fuel moisture codes. Then, for the remaining covariates, we used recursive feature selection using 5-fold cross validation (CV) and the RF algorithm in caret (Kuhn, 2008) in the statistical software R (R Development Core Team, 2025) to identify the combination of covariates that resulted in the highest accuracy metrics. This process resulted in the selection of 14 covariates for inclusion in the final model, with the terrain derivatives of aspect, diurnal anisotropic heat (DAH), wind exposure and SAGA Wetness Index being removed from the training dataset.

Boxplots shown in Figures 7, 8 and 9 show the range of values of selected, continuous covariates for ignition vs non-ignition training samples for selected fuel types and seasons, while barplots in Figure 10 give the counts of ignitions vs non-ignition training samples for the selected, categorical covariates. Overall, the sampling approach used resulted, for most covariates and fuel types, in distinct differences in their covariate ranges. For example, ignition samples of Conifer fuel type and fire date in season T2 (May to September) were located at lower elevations and had greater FWI values than the respective non-ignition samples of the same fuel type and for the same fire date season (Figure 7b). These observed differences ensured that the training dataset was appropriate for this particular modelling approach. Descriptive statistics for all continuous covariates for ignition and non-ignition training samples are given in Table A1 in the Appendix.

Final model settings

We randomly selected 70% of the virtual sample points for training the model (1,700 ignition and non-ignition samples), leaving 30% for internal validation (728 points not used for training the models). We tuned and trained a random forest probability model (Malley et al., 2012) using the ranger method (Wright and Ziegler, 2017) in caret in R. The main model hyperparameters, number of covariates (predictors=*p*) randomly selected at each node (mtry), minimum node size (min.node.size) and number of trees to grow (ntree) were tuned and determined using a 5-fold CV for mtry=p^0.5, p/4, p/3, and p/2, min.node.size=5,1 0, 15 and ntree=500, 750 and 1,000. Hyperparameter values that gave the model with the greatest accuracy were mtry=5, min.node.size=5 and ntree=500.

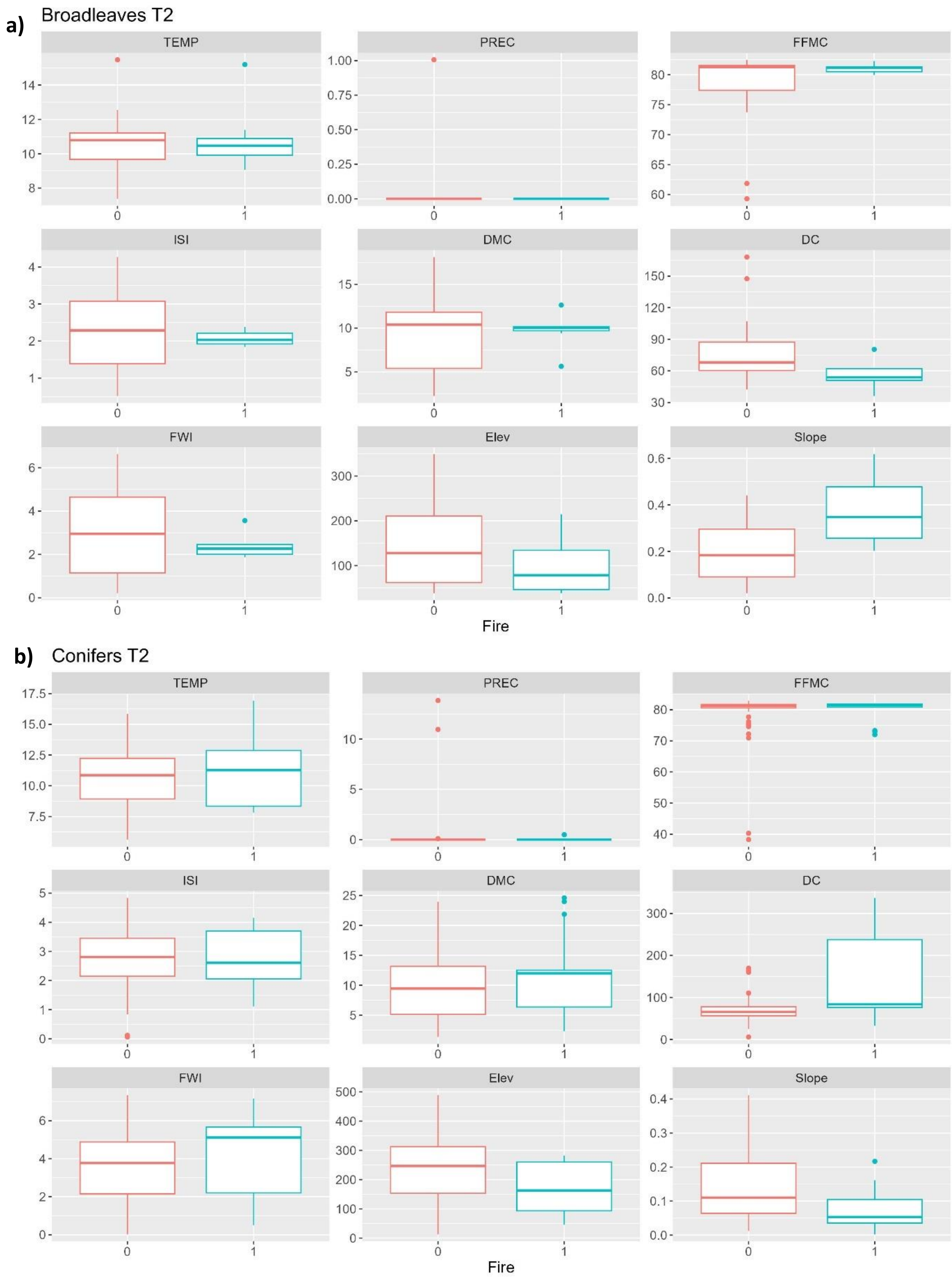


Figure 7. Boxplots of selected, continuous covariates for ignition (Fire=1) and non-ignition (Fire=0) training samples with fire dates in season T2 (May to Sep) and fuel types a) Broadleaves and b) Conifers.

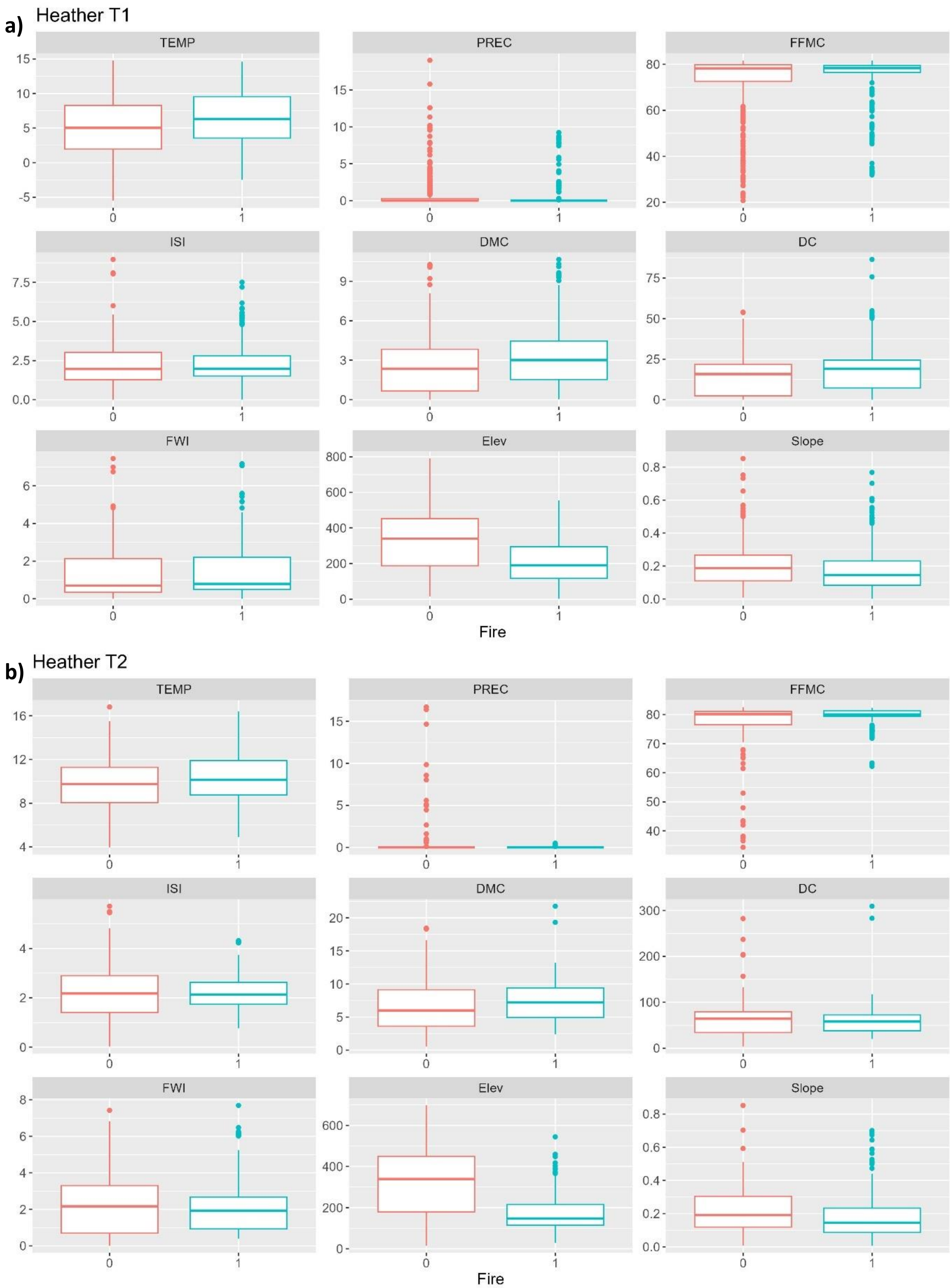


Figure 8. Boxplots of selected, continuous covariates for ignition (Fire=1) and non-ignition (Fire=0) training samples with Heather fuel type and fire dates in season a) T1 (Jan – Apr) and b) T2 (May to Sep).

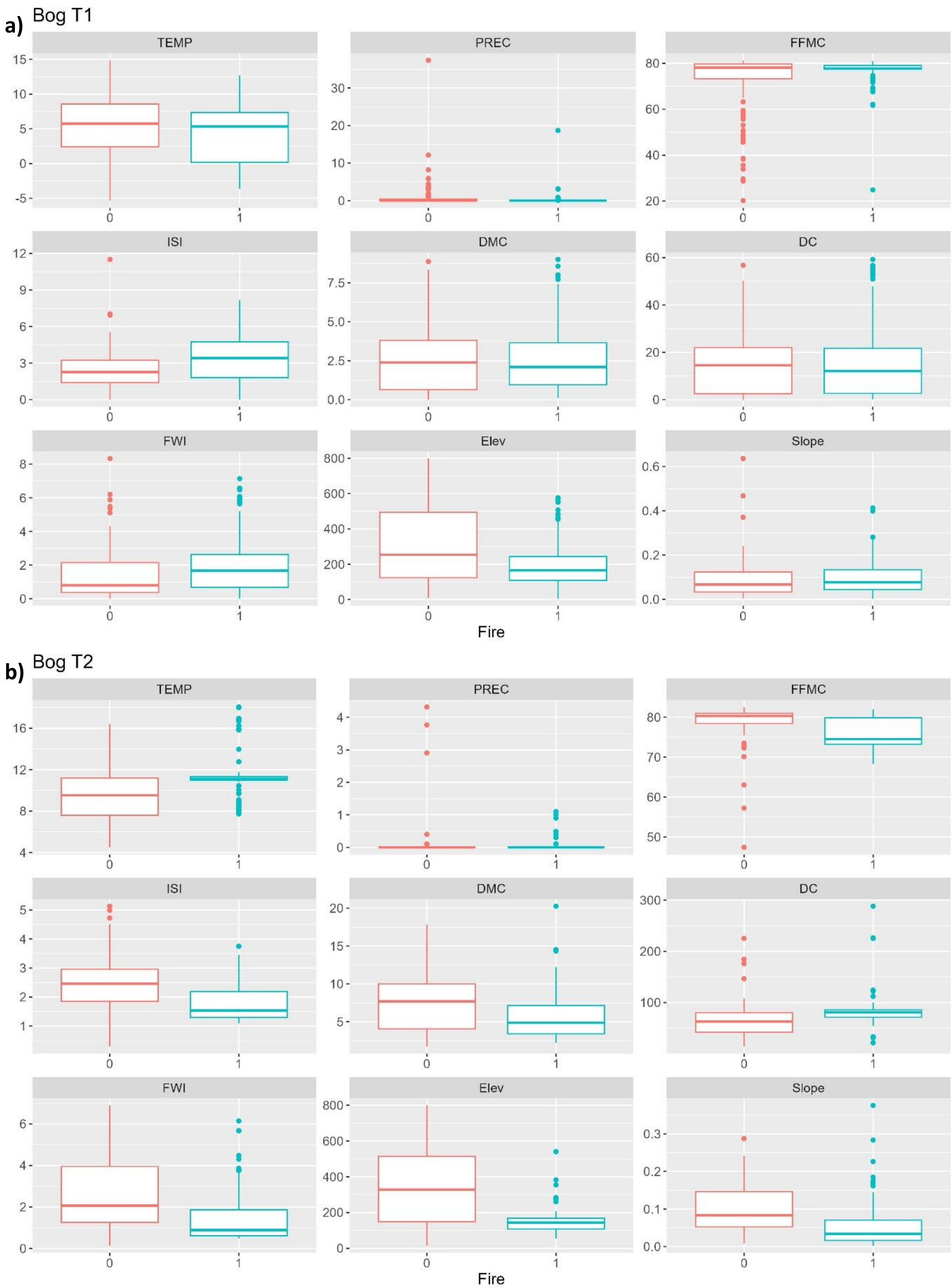


Figure 9. Boxplots of selected, continuous covariates for ignition (Fire=1) and non-ignition (Fire=0) training samples with Bog fuel type and fire dates in season a) T1 (Jan – Apr) and b) T2 (May to Sep).

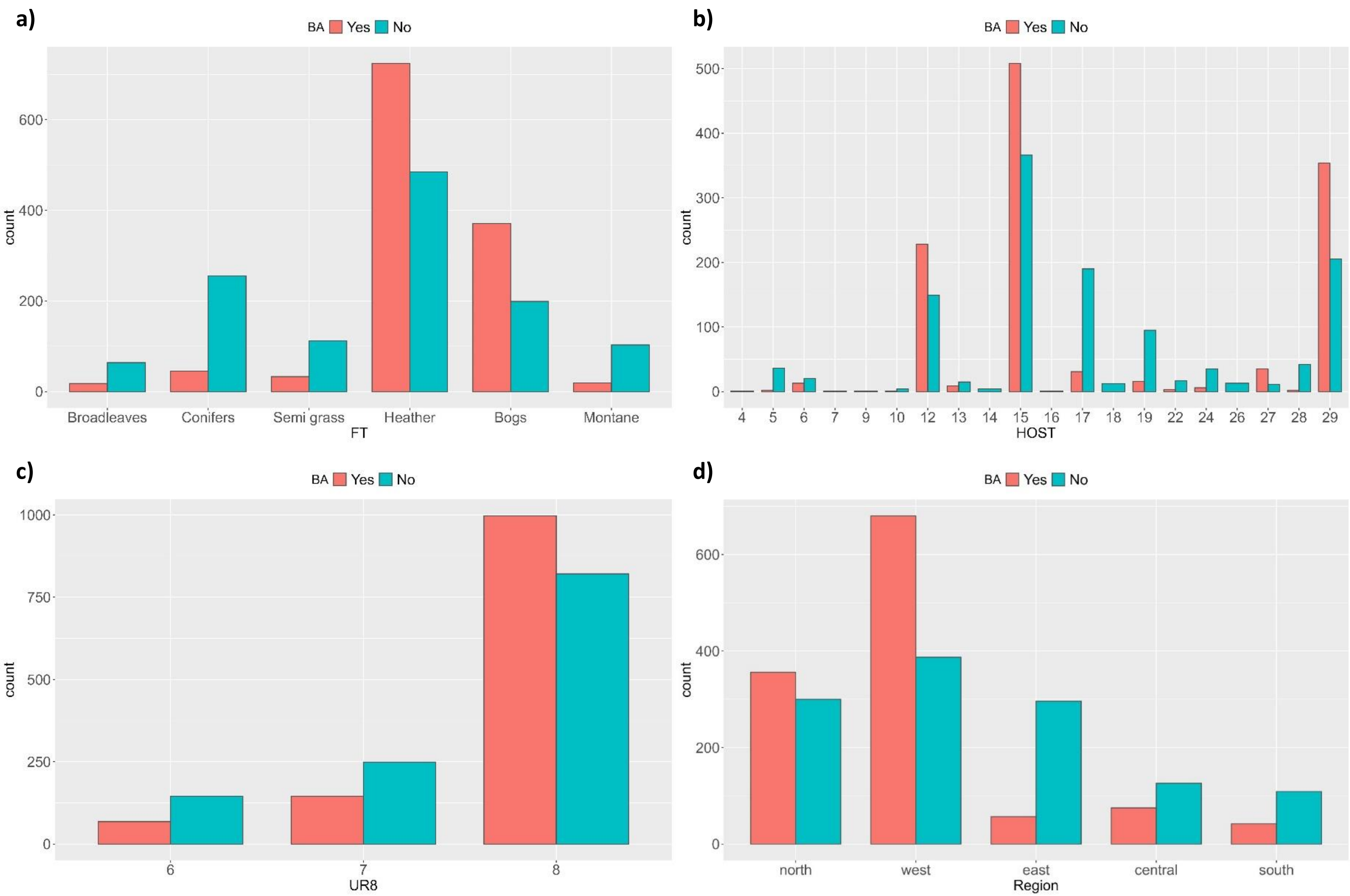


Figure 10. Counts of ignition (BA=Yes) and non-ignition (NA=No) samples by categories of selected discrete covariates a) Fuel type, hybrid map of LCS88 and NFI2015; b) Hydrology of Soil Types (HOST) classes; c) Urban-Rural Classification; and d) Regions.

Simulation of future fire danger in the Cairngorms National Park

Study area

The Cairngorms is part of an international family of National Parks and is the largest in the UK, at 4,528 km^2 (Figure 12a). The Cairngorms National Park (CNP) is located in the Scottish Highlands, and covers parts of Aberdeenshire, Moray, Highland, Angus and Perth and Kinross. Spatial assessments of future fire danger in the Park were conducted in the area covered by this study's selected land covers/fuel types that covered 4,168 km^2 or ~92% of the Park total area. Land cover/fuel type composition within the CNP study area was determined using the same hybrid approach used previously for the generation of the training samples, but in this case the LCS88 map was combined with the latest available (2023) NFI map for Scotland to provide an accurate representation of current tree coverage within the Park (Figure 12b). Based on the generated land cover map, Heather was the dominant fuel type covering 1,966 km^2 or 47% of the CNP study area, followed by Bogs (825 km^2 or 20% cover), Montane vegetation (542 km^2 or 13% cover) and Conifers (531 km^2 or ~13%), while Seminatural grasslands and Broadleaves covered ~4.5% (189 km^2) and 3% (115 km^2) of the study area, respectively (Figure 11).

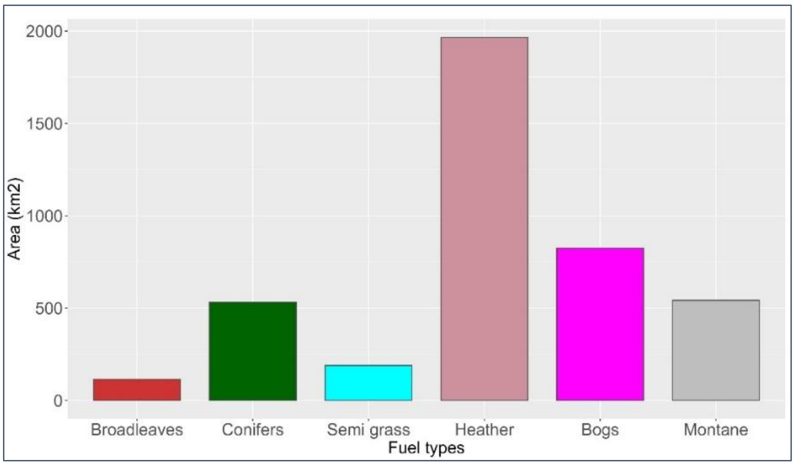


Figure 11. Areas of selected Land use/Fuel types within the Cairngorms National Park based on the hybrid LCS88 – NFI_2023 map.

Peaty podzols and gleys (HOST15) covered the greater area in the CNP study area (1,029 km^2 or ~25% cover), followed by Humus-iron podzols (HOST17, 932 km^2 or 22% cover) and Upland blanket bogs (HOST29, 785 km^2 or 19% cover). Almost 3,500 km^2 (~84% cover) in the CNP study area were classified as Very Remote Rural areas (Fold=8) based on the Urban Rural Classification, with another 16% (or 679 km^2) being classified as Remote Rural Areas (Fold=7), while almost all of the study area in the Park (4,153 km^2 or 99.6%) was within the East region, as specified in this study (see Figure 6d). The study area has a quite varied terrain (Figures 12c and 12d), with more than half of the study area (56%) lying on altitudes greater than 500m above sea level.

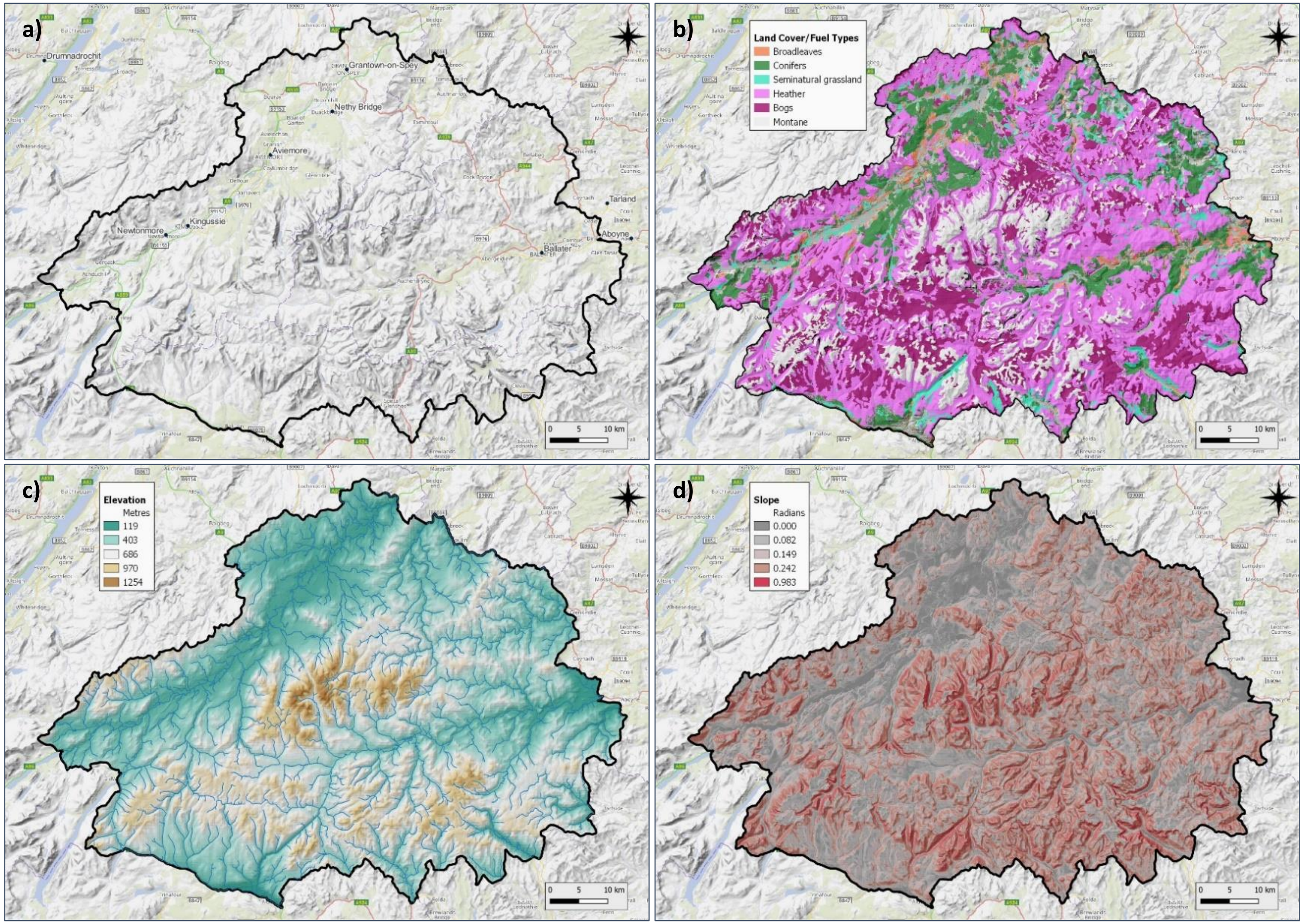


Figure 12. Maps of a) Boundary of the Cairngorms National Park; b) Land cover/fuel type based on hybrid LCS88 and NFI2023; c) Elevation range (in m) and d) Slope gradients (in radians). © Crown copyright and database right (2025). All rights reserved. The James Hutton Institute, Ordnance Survey Licence Number AC0000812928

Climate and future fire weather

Recent analysis looking at observed changes in the CNP and projected climate change using four UKCP18 Ensemble Members (Rivington and Jabloun, 2024) found that the climate in the Park has already changed since the 1960-1989 period. These changes are spatially and temporally variable, with the winter months becoming both wetter and warmer, whilst summer months have become warmer. Future projections indicate that the Park will experience further warming over the coming decades, as well as seasonal and spatial shifts in precipitation distribution. A key finding was that large sections of the Park are likely to experience spring and summer seasons when there is a potential decrease in meteorological water (evapotranspiration > precipitation), meaning that areas that have previous had a meteorological water surplus could experience a deficit in the future. This will increase the risk of drier soils and vegetation, with consequences on ecological functions and fire danger. This analysis also calculated climate extreme indicators that are relevant to fire weather characteristics, such as the number of Consecutive Dry Days (CDD: maximum length of a dry spell in any month when precipitation is less than 1mm per day). During the 1990 - 2019 period, which includes the historical fires used in the training dataset, for most months CCD were greater in the northern and eastern areas of the Park, such as in the valleys of the Spey and Dee rivers (Figure 13a). Despite variability between the climatic projections used, they seem to agree that most of the area of the Park is expected to see a decrease in CDD (i.e., experience wetter conditions) during late winter and spring months, with an increase in CDD projected in late summer and early autumn (Figure 13b).

Daily fire weather codes and indices for the 2020 - 2049 period were calculated using CHESS-SCAPE climate data set (Robinson et al., 2023b), which provides several physical climate variables over the UK for the period 1980 - 2080 at 1 km spatial resolution. It is derived from four ensemble members of the UKCP18 12 km Regional Climate Model (RCM) (the same raw data used by Rivington and Jabloun, 2023), bias-corrected and downscaled to 1 km (comparable but different method than Rivington and Jabloun, 2023) and extended to cover four different realisations of future climate for each of four different representative concentration pathway (RCP) scenarios: RCP2.6, 4.5, 6.0 and 8.5. We selected the ‘stringent’ emissions scenario, RCP8.5, for consistency with the climate trends work of Rivington and Jabloun (2023), and selected Ensemble Member 1 (EM01) mainly because it is in the middle of the range of temperature increases (about 2.3 °C) and the largest decrease in annual precipitation (about 7.5 %) among the four ensemble members across the CNP. Moreover, EM01 has one of the smallest increases in spring (March-May) temperature (Robinson et al., 2023b), the smallest increase in winter (December-February) and the largest decrease in autumn (September-November) precipitation. It also has a very small decrease in spring precipitation and one of the smaller decreases in the summer (June-August).

We downloaded and built a database of NetCDF files at 1 km resolution aligned to the Ordnance Survey (OS) British National Grid) of gridded daily air temperature (°C), relative humidity (%), wind speed (m s^{-1}), and precipitation (mm) for the 2020 - 2049 period and calculated the required fire weather indices (FFMC, ISI, DMC, DC and FWI) for the 4,697 1 km grid squares covering the study area in the CNP using the cffdrs R-package. All these calculations were performed in the UK Crop Diversity high-performance computing platform. Figure 14 gives monthly maps of the 50th (median) and 95th percentile (used as indicator of extreme fire weather as in Perry et al., 2022) for the selected fire weather indices using the daily calculated values at each 1 km grid square and for the 2020 - 2049 period. Visual inspection of these maps reveals some clear patterns of fire weather spatial variation, with higher mean and extreme fire weather index values found mainly in the northern and eastern parts of the Park, while for DMC and DC (Figures 14c and 14d), higher values are observed within the valleys of the Spey and Dee rivers in most months.

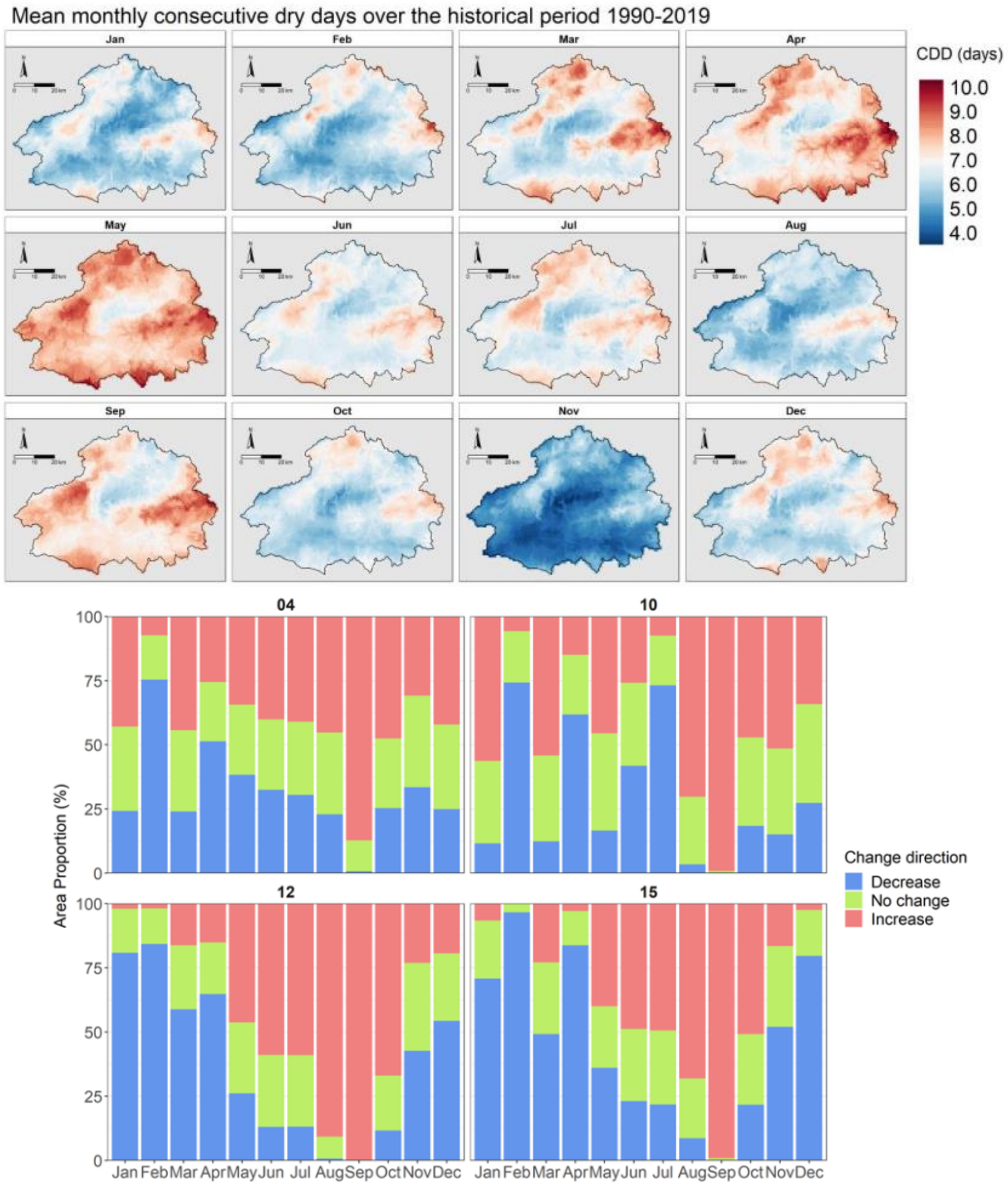
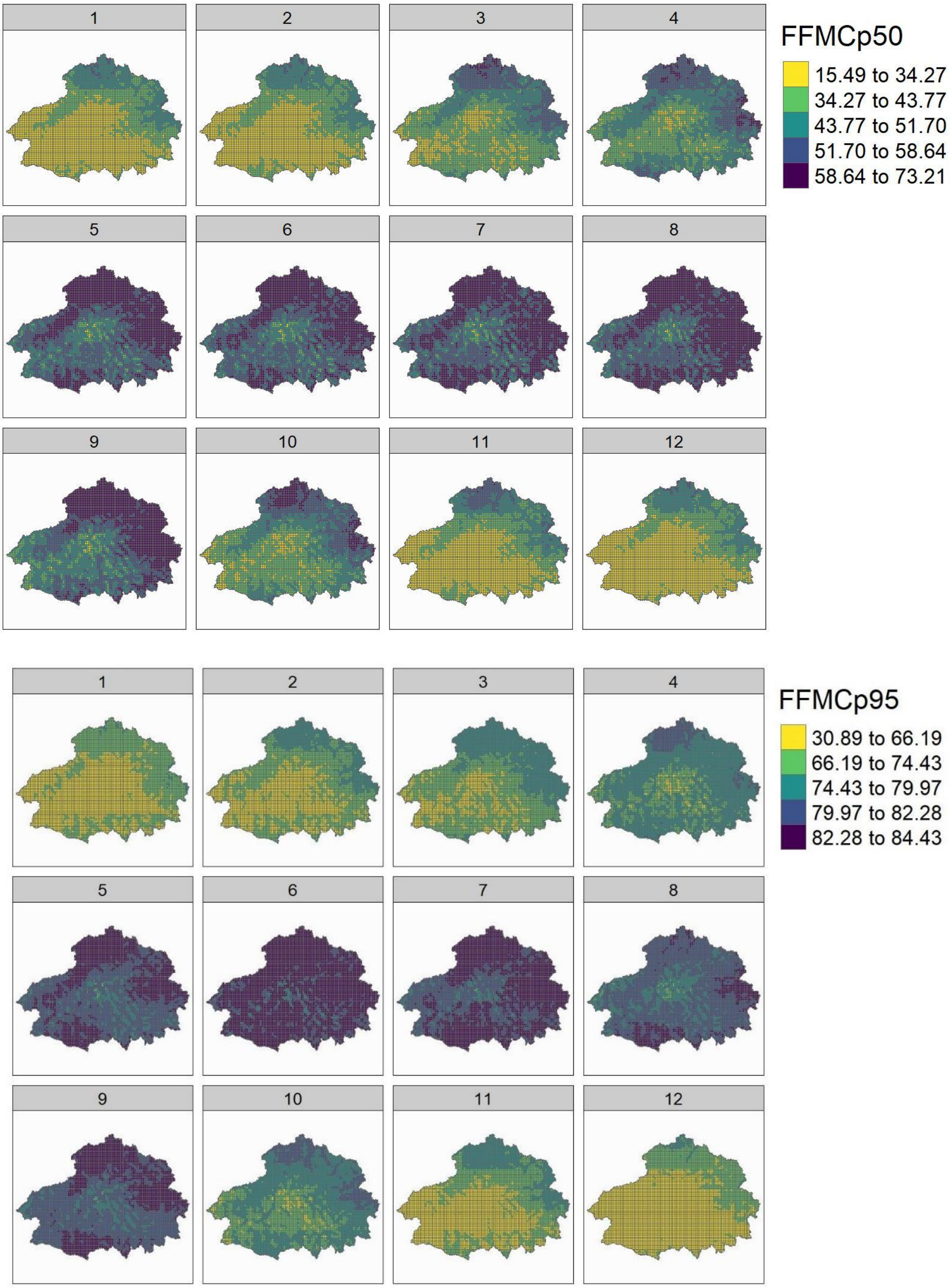


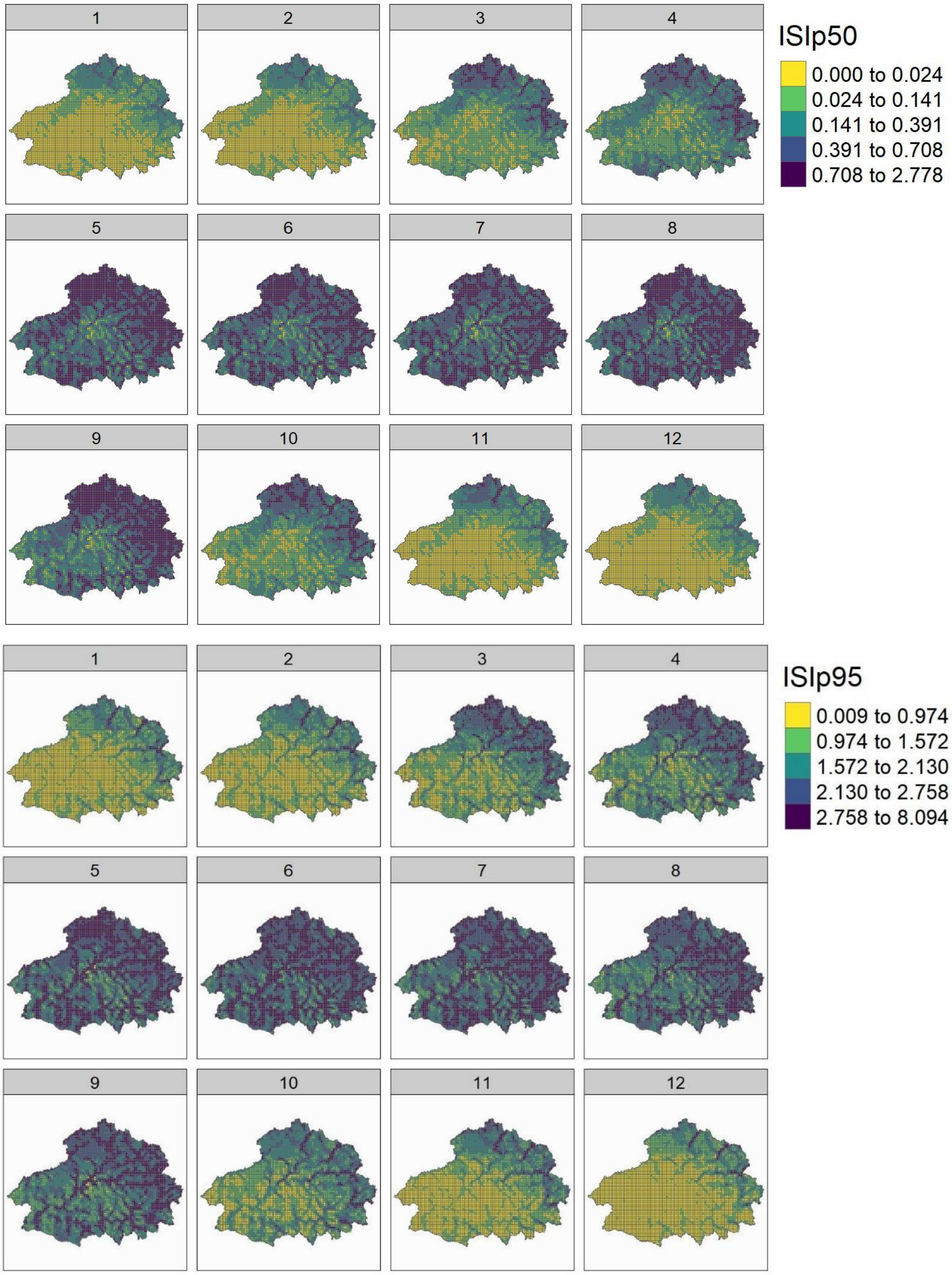
Figure 13. a) Observed mean monthly Consecutive Dry Days over the period 1990 – 2019 and b) Cairngorms National Park land area proportion (%) for the mean monthly number of Consecutive Dry Days for the future period 2020-2049 based on EM04, EM10, EM12 and EM15 (Rivington and Jabloun, 2024).

The covariate data layers were converted to grid layers at 250m resolution, which was considered appropriate for a) harmonising data layers with variable resolution (e.g., terrain at 50m pixel vs climate at 1km pixel) and b) preserving the level of spatial variation of the land cover map that was available in vector (polygon) format. The stacked grid layers were converted to a data frame and were inputted to the RF fire danger model to generate daily probabilities of fire occurrence for the 2020 - 2049 period and for each of the 66,692 250m grid cells covering the study area in the Park.

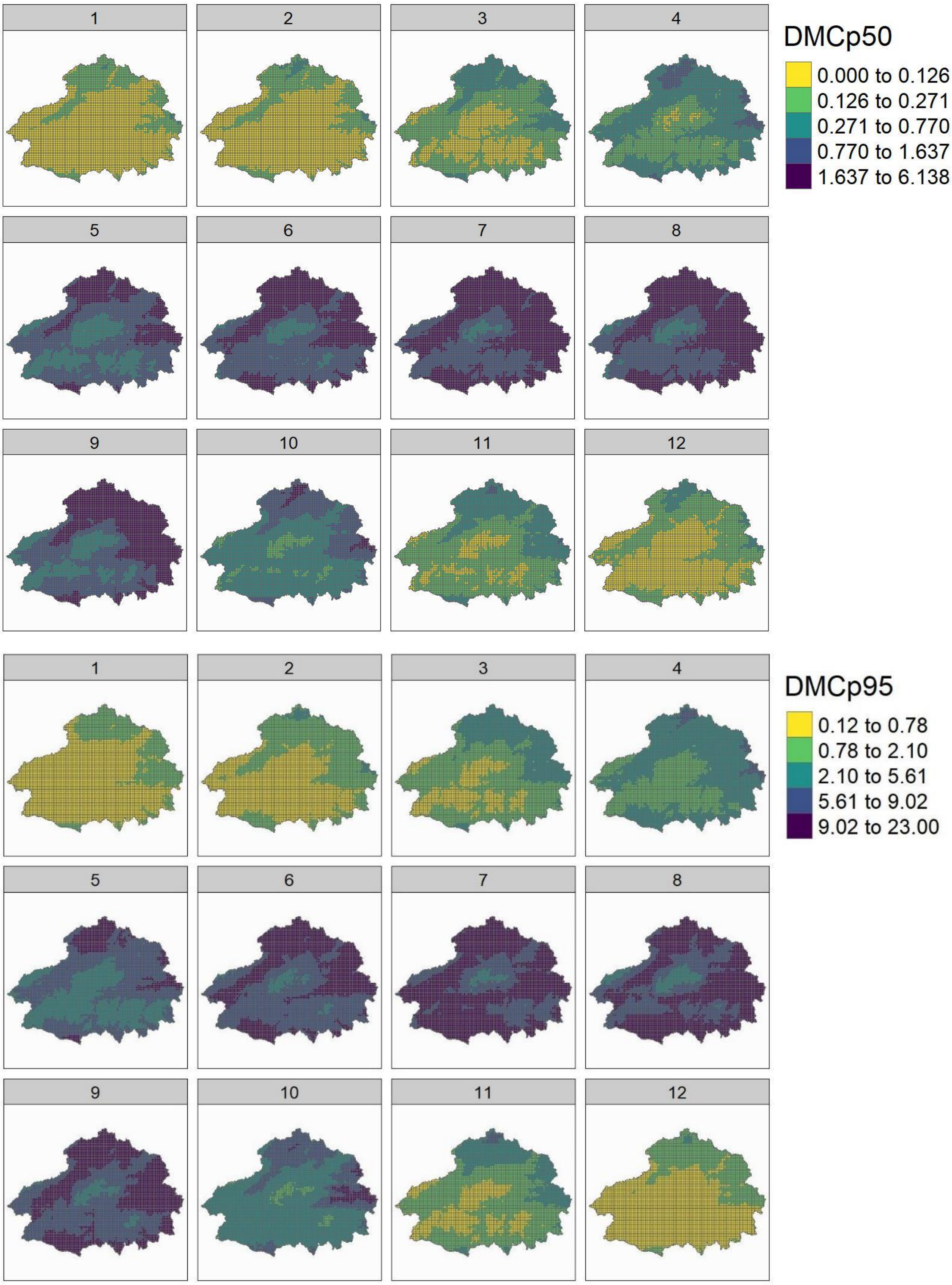
a)


1
2
3
4
5
6
7
8
9
10
11
12
FFMCp50
15.49 to 34.27
34.27 to 43.77
43.77 to 51.70
51.70 to 58.64
58.64 to 73.21
1
2
3
4
5
6
7
8
9
10
11
12
FFMCp95
30.89 to 66.19
66.19 to 74.43
74.43 to 79.97
79.97 to 82.28
82.28 to 84.43

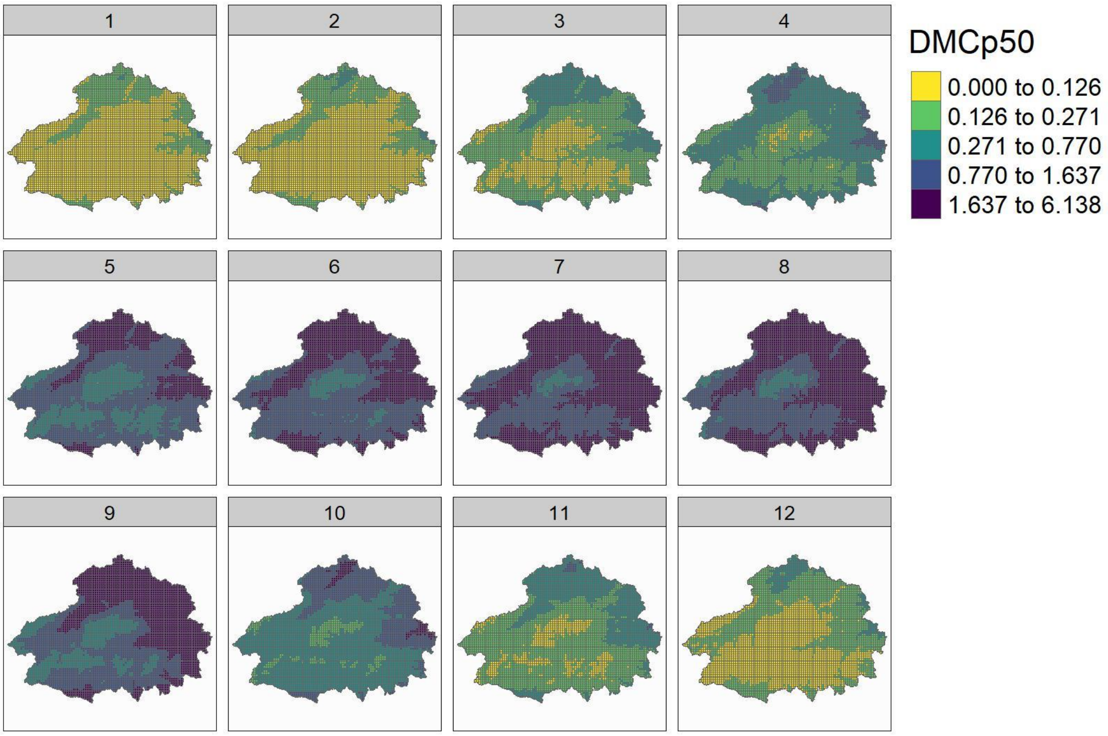
b)


1
2
3
4
5
6
7
8
9
10
11
12
ISIp50
0.000 to 0.024
0.024 to 0.141
0.141 to 0.391
0.391 to 0.708
0.708 to 2.778
ISIp95
0.009 to 0.974
0.974 to 1.572
1.572 to 2.130
2.130 to 2.758
2.758 to 8.094

c)


1
2
3
4
5
6
7
8
9
10
11
12
DMCp50
0.000 to 0.126
0.126 to 0.271
0.271 to 0.770
0.770 to 1.637
1.637 to 6.138
1
2
3
4
5
6
7
8
9
10
11
12
DMCp95
0.12 to 0.78
0.78 to 2.10
2.10 to 5.61
5.61 to 9.02
9.02 to 23.00

d)


1
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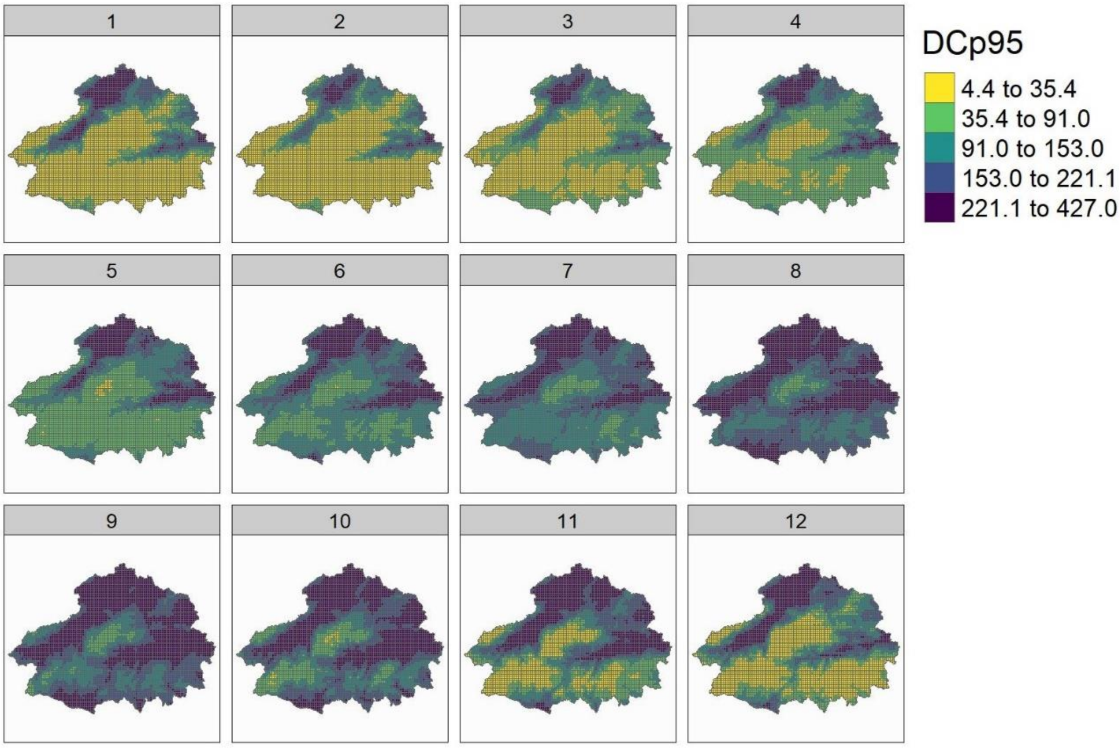
9
10
11
12
DMCp50
0.000 to 0.126
0.126 to 0.271
0.271 to 0.770
0.770 to 1.637
1.637 to 6.138


1
2
3
4
5
6
7
8
9
10
11
12
DCp95
4.4 to 35.4
35.4 to 91.0
91.0 to 153.0
153.0 to 221.1
221.1 to 427.0

e)

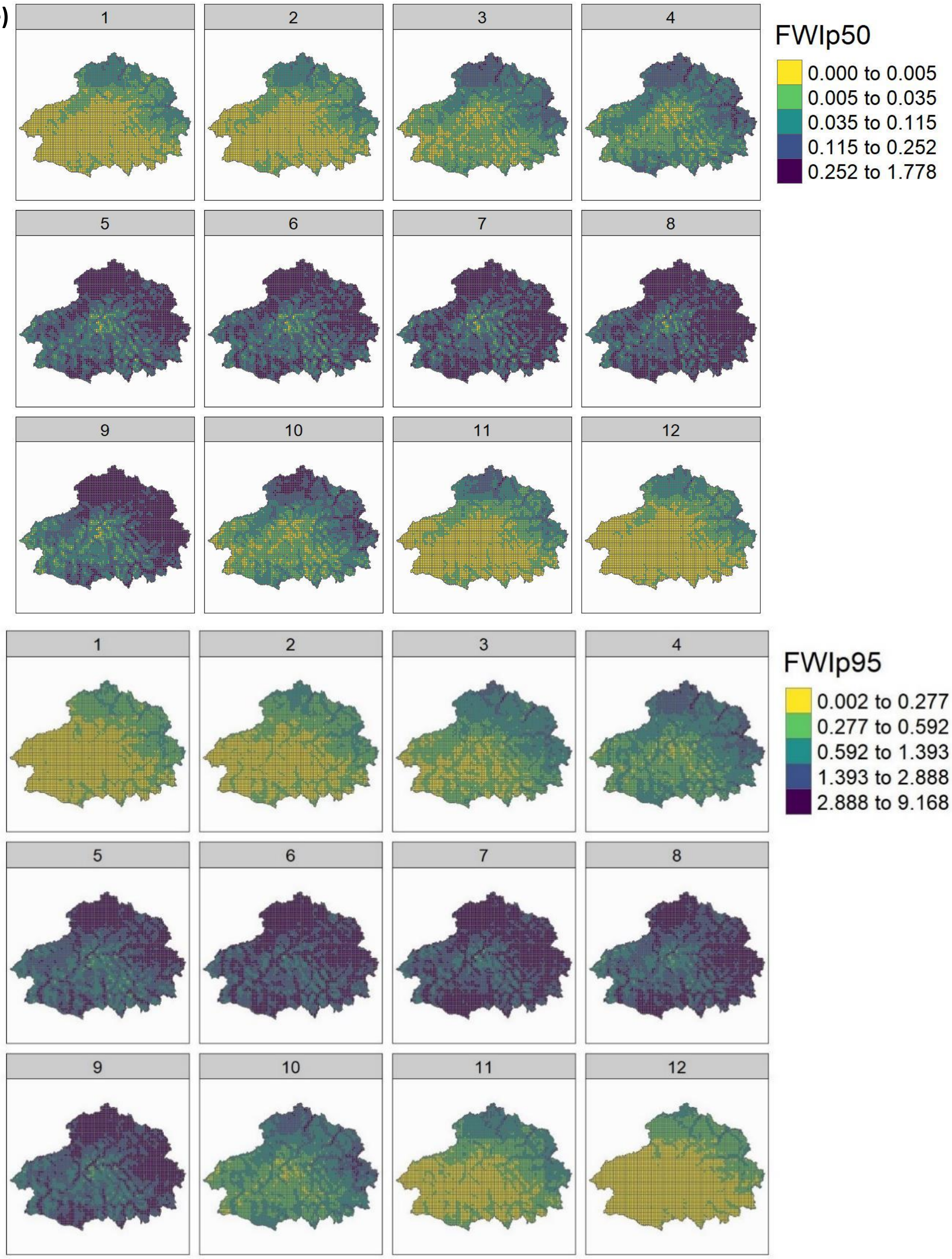


Figure 14. Monthly maps of 50th and 95th percentile values of selected Fire Weather Indices a) FFMC, b) ISI, c) DMC, d) DC and e) FWI, calculated using daily calculated values using CHESS-SCAPE climate at 1 km resolution for the 2020 - 2049 period.

Results & Discussion

Model performance

Overall, the trained model performed well with an OOB prediction error of 0.106, indicating an accuracy of almost 90% in the OOB sample. Using a probability of fire occurrence threshold of 0.5 (i.e., the model predicts "fire" if there is a >=50% probability of a fire occurring at this location), the model predicted fire in 751 of the 847 ignition samples and non-fire in 706 of the 853 non-ignition samples used for model training. Results of internal testing using the left-out samples using the same probability threshold showed high sensitivity (0.855), i.e., the avoidance of false negatives (predicting non-fire where a fire had actually occurred). The model's specificity was also high (0.876), demonstrating a good ability to avoid predicting false positives, i.e., predicting fire at the location of a non-ignition sample. Overall balanced accuracy was 0.865. Table 3 gives the accuracy statistics.

Table 3. Accuracy statistics of the fire danger model calculated using the left-out samples.

	Predicted non-fire	Predicted fire
Actual non-fire	312 (True negative)	45 (False positive)
Actual fire	53 (False negative)	318 (True positive)

As Dixon and Chandler (2019) note, selection of a probability threshold for ignition or fire occurrence depends on user needs, considering that the cost of a false positive is likely not equal to the cost of a false negative. For example, attending a call-out in which no ignition has occurred may be preferable to not attending a call-out in which there is an ignition. Therefore, in the case of fire suppression it might be preferable to set higher thresholds to reduce the likelihood of a false negative (the model predicts no ignition when actually there is an ignition). In this study the objective was not fire suppression but the spatial assessment of future fire danger and this required defining appropriate fire danger classes based on the generated probabilities of fire occurrence. The formulation of these classes was informed by the model predictions for both the train and independent samples, which showed that most misclassifications (false negatives and false positives) occurred for predicted probabilities between 0.45 to 0.55, while true positives and true negatives in most times had prediction probabilities >0.60 and <0.40, respectively. Hence, the following fire danger classes were defined:

- Very Low (VL): <=0.15 probability.
- Low (L): >0.15 - <=0.45 probability.
- Moderate (M): >0.45 - <=0.55 probability.
- High (H): >0.55 - <=0.85 probability.
- Very High (VH): >0.85 probability.

Relative importance of model predictors (covariates) was assessed using the metric of mean decrease in accuracy (MDA) that is calculated automatically by the RF algorithm. Elevation was the most important model predictor (Figure 15), which highlights the importance of both weather and climatic patterns and accessibility for fire occurrence prediction. The Urban Rural classification scored relatively low in terms of MDA, but this can be explained by the fact that training samples were located mostly in two folds (67: Remote Rural and 8: Very Remote Rural), and this lack of variability resulted in the predictor getting a lower MDA. On the contrary, fuel type was the second most important predictor, which reflects the known differences in fire danger for different fuels. Of the fire weather indices used, FFMC and DMC were the most important overall, while daily temperature was found to be more important than DC, FWI and ISI. Seasonality was found to be the least important predictor; this is probably driven by the imbalance in the training dataset since most past fires used to develop the train samples occurred in Season T1, while very few occurred in Season T3. It is worth noting though that RF model predictions are based on identifying non-linear interactions between all covariates used, therefore their relative importance was expected to vary substantially by e.g., combinations of fuel type and season, compared to the overall predictor importance presented here.

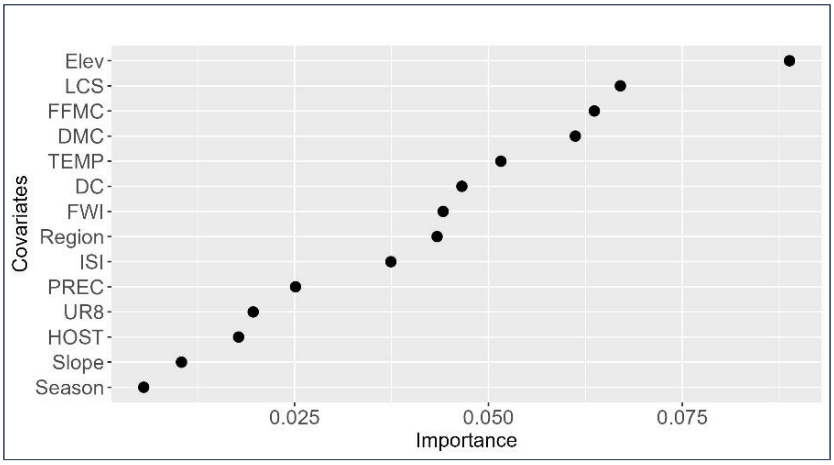


Figure 15. Importance of covariates used for ignition risk modelling based on MDA.

Spatial assessments of future fire danger

Mapping approach

Fire danger simulations comprised of predicted daily probabilities of fire occurrence for the 2020 - 2049 period and for each of the 66,692 250m grid cells covering the extent of the CNP study area. To conduct the mapping assessments of future fire danger and visualise and communicate them in an effective way, we devised the following approach:

- We assigned the daily predicted probabilities of fire occurrence to the formulated 5 fire danger classes: VL, L, M, H and VH.
- We counted the number of days falling within each danger class at each 250m grid square separately for the three Seasons T1, T2 and T3, and calculated respective proportions. For example, if at a specific 250 grid square 360 days were found to have Moderate fire danger for Season T1 (Jan - Apr) for the 2020-2049 period (total count of 3,600 days), then the proportion of days in that grid square with Moderate fire danger for Season T1 was 10% (360/3,600 x 100). For the purposes of this work, this 10% was interpreted as fire danger being on average Moderate in that grid square for approximately 3 days a month between January to April, although great variability is expected within the 30-year period covered by the climatic projection used.
- The generated proportions for each fire danger class were used to produce spatial layers and respective maps. They were also used to calculate descriptive statistics for selected covariates and generate plots to explore patterns of covariate ranges by fire danger classes that were identified by the model for fire occurrence prediction.

Results of the mapping assessments following this approach are presented below individually for each of the 3 Seasons (T1, T2 and T3) used in this study, with the objective to a) identify areas (hotspots) of future fire danger within the CNP and b) identify drivers of fire danger within these hotspot areas for different fuel types. Hotspot areas were defined as those where >10% of days within a given season had Moderate and/or High fire danger class (there were very few days with a Very High predicted fire danger); this threshold was considered sensible based on the results of the fire danger simulations and denotes moderate to high fire danger for at least 3 days each month. Hotspot areas, and the respective fuel types are given in maps, while boxplots visualise the range of fire weather index values by danger class for different fuels in these hotspot areas. In addition, monthly boxplots of continuous covariates for the whole area of the CNP (within and outside of these hotspot areas) are given in Section A2 of the Appendix.

Season T1 Fire Danger Assessment

In Season T1, which covers the late winter to early spring period (Jan – Apr), 966 250m grid cells were found to have >10% days falling within the Moderate fire danger class, covering an area of ~60 km^2 or just 1.45% of the study area, with ~ 15% of these grid cells having >20% or >6 days a month on average falling within the Moderate Fire Danger class (Figure 16a). Only one (1) grid cell was found to have >10% days falling within the High fire danger class. Regarding fuel type, most grid cells (*n*=820) had Heather as their fuel type, and in the remaining 146 grid cells the fuel type was Bogs (Figure 16b). Most of this area was located close on the northern boundary of the Park around the wider Grantown on Spey area and mostly on the hills north of the A938 section between Dulnain Bridge and Duthil and just to the south of Speybridge, with a smaller area was located north of Loch Davan close to the eastern boundary of the Park. Most of these grid cells were found on upland blanket peat (HOST29, *n*=333), unconsolidated sand and gravels on valley hillslopes (HOST5, *n*=287) and peaty podzols or peaty gleys (*n*=135). Also, 97% this area was located in Remote Rural Areas based on the Urban Rural classification (Fold=7).

Regarding differences in covariate values within the fire danger classes in these areas, areas with simulated Moderate or High fire danger were on lower elevation and slope gradients than areas with Very Low or Low fire danger for both Heather and Bog fuel types. These differences become more evident when comparing simulated fire danger for the whole extent of the CNP (Appendix A2). For example, in Heather areas, mean elevation in areas with simulated Moderate and High simulated fire ranged from 311m to 396m, while in areas of Very Low to Low fire danger mean elevation ranged from 396m to 575m. In addition, simulated fire danger was always Low or Very Low in areas above ~650m.

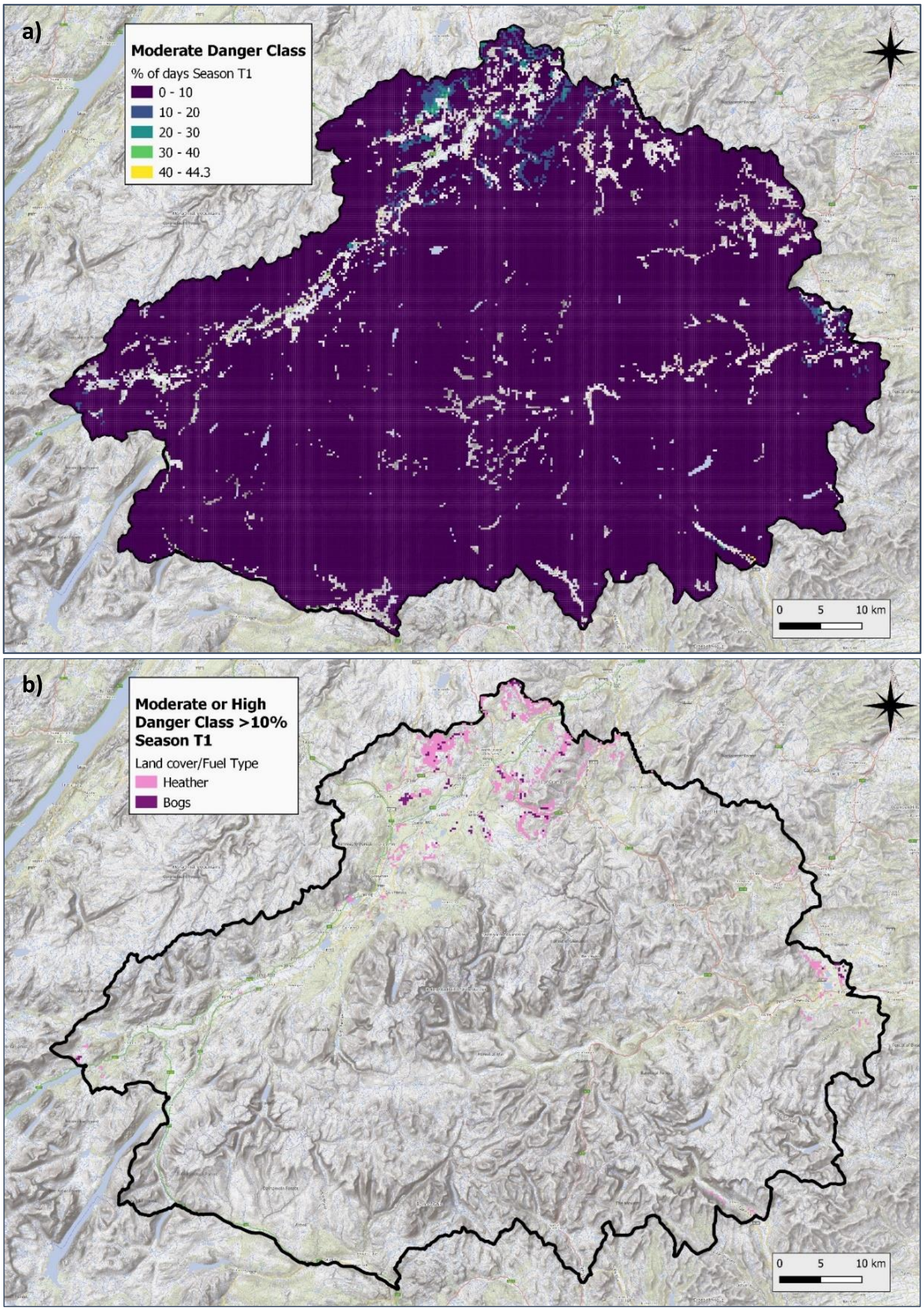


Figure 16. Map of a) Proportions (%) of Season T1 days within the Moderate Fire Danger Class and b) Fuel Type of areas falling within the Moderate or High Danger Class for >10% of Season T1 days, for the 2020-2049 period in the Cairngorms National Park.

Looking at the influence of fire weather, FFMC and ISI and to a lesser extent DMC seemed to be driving simulated fire occurrence probabilities in both Heather and Bog areas (Figure 17 and Appendix A2). High FFMC and DMC represents drier conditions in the moss and litter layer and in peaty topsoils, respectively, while high ISI indicates windy conditions. In the hotspot areas on Heather, mean FFMC and ISI in days with Moderate or High simulated fire danger was 67-71 and 1.6-1.9, respectively, compared to 40-48 and 0.1-0.6, respectively for days with Very Low to Low simulated fire danger; these differences were similar when looking at simulated fire danger for whole of the CNP. However, it is also evident that there is considerable overlap in fire weather index values between all fire danger classes, and this is driven by the fact, which is reflected in the training dataset, that wildfires in Scottish moorlands in late winter and early spring have been found to occur in lower FFMC (relatively high fuel moisture content). This might have caused confusion in model predictions. At the same time, the fact that fire danger was simulated to be Moderate or High for >10% of days in the 2020-2049 period in a relatively small area, despite the model using sensible FFMC and ISI thresholds for assigning greater fire danger, implies the prevalence of wet and/or low wind conditions on average in the daily time series for Season T1.

Regarding the spatial co-occurrence of identified hotspots areas with mapped muirburn areas, 63% and 41% of hotspot areas on Heather and Bog, respectively, were found on mapped muirburn areas. Season T1 (Jan – Apr) is within the standard muirburn season in Scotland that runs from October 1st to April 15th. Although the link between muirburns and wildfires in Scotland is uncertain, it is suggested that extra caution is exercised in these areas during the burns to minimise any likelihood of fire spreading accidentally.

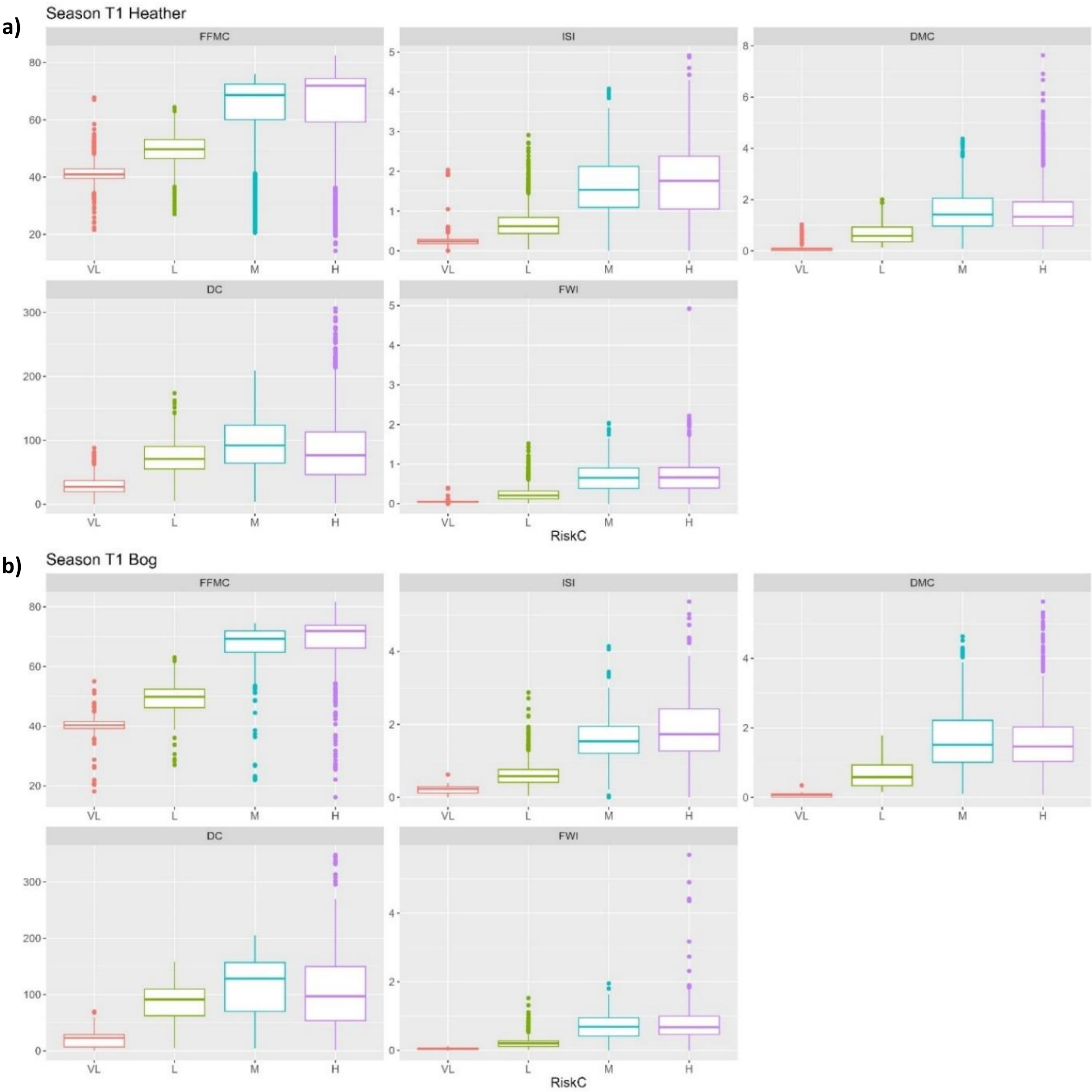


Figure 17. Boxplots of calculated Season T1 daily Fire Weather Index values by predicted Fire Danger classes for a) Heather and b) Bog areas in the Cairngorms National Park.

Season T2 Fire Danger Assessment

In Season T2, which covers the late spring to early autumn (May – Sep) and when all vegetation is live, the model predicted a substantial increase of hotspot areas, i.e., >10% days falling within the Moderate of High fire danger class. Overall, 3,347 250m grid cells were identified as fire danger hotspots, covering an area of ~209 km^2 or 5% of the study area, with ~ 15% of these grid cells having >20% or >6 days a month on average falling within the Moderate fire danger class (Figure 18a). Only three (3) grid cells were found to have >10% days falling within the High fire danger class. Regarding fuel type, Conifers were the fuel type for ~ 40% of this area, followed by Heather (28%), Seminatural grassland and Broadleaves (both 11%), whilst 194 (~6%) grid cells were on Bog and only two (2) on Montane vegetation (Figure 18b). Most of the identified fire danger hotspot area was located along the main floodplains and valleys of rivers Spey and Dee, in parts of the Abernethy Forest and in smaller areas in Glen Lochy and the Muir of Dinnet. Most of these grid cells were found on unconsolidated sand and gravels on valley hillslopes (HOST5, *n*=1,172), followed by upland blanket peat (*n*=680) and peaty podzols or peaty gleys (*n*=365). Also, 67% this area was located in Remote Rural Areas based on the Urban Rural classification (Fold=7) and 33% in Very Remote Rural Areas (Fold=8).

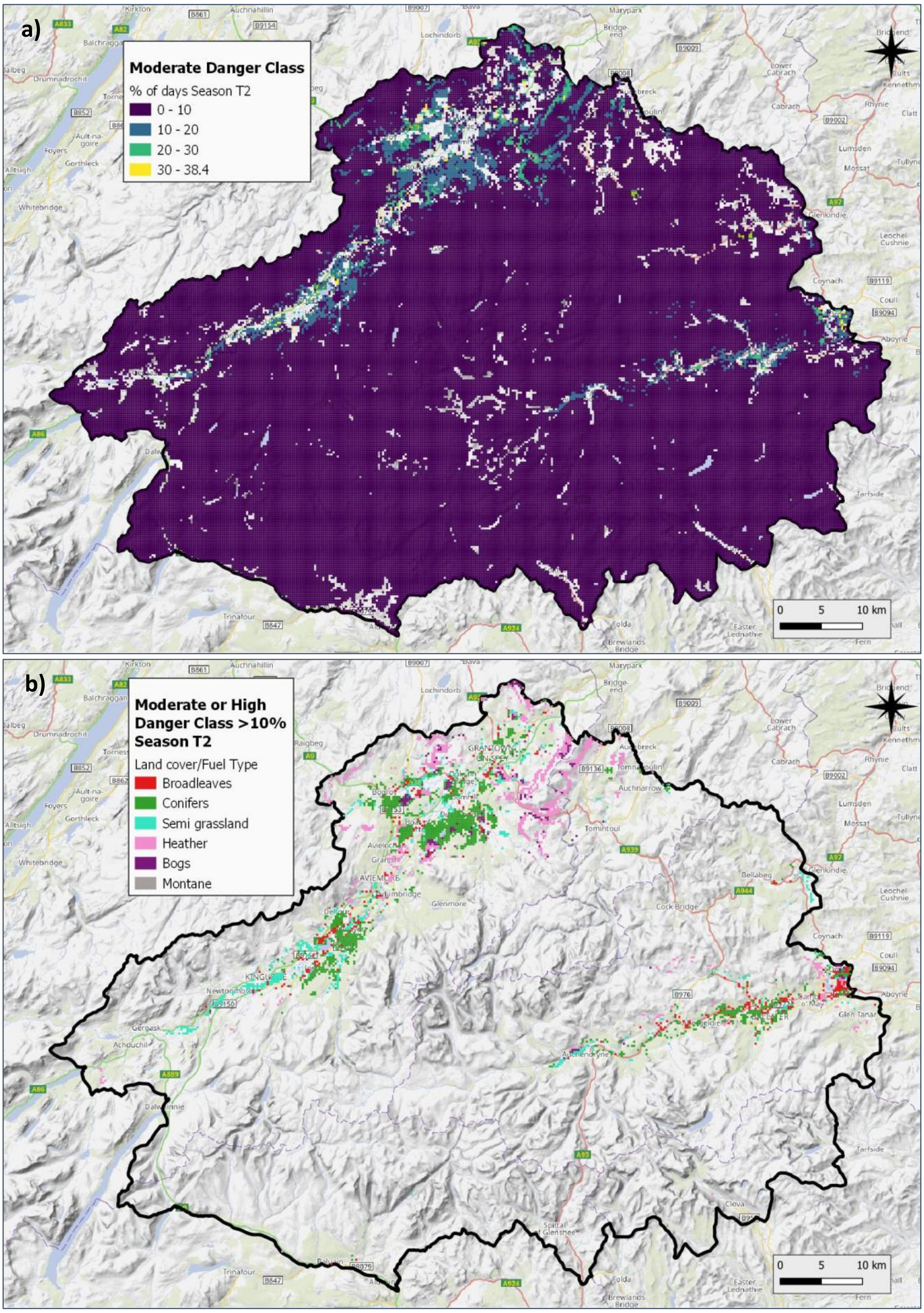
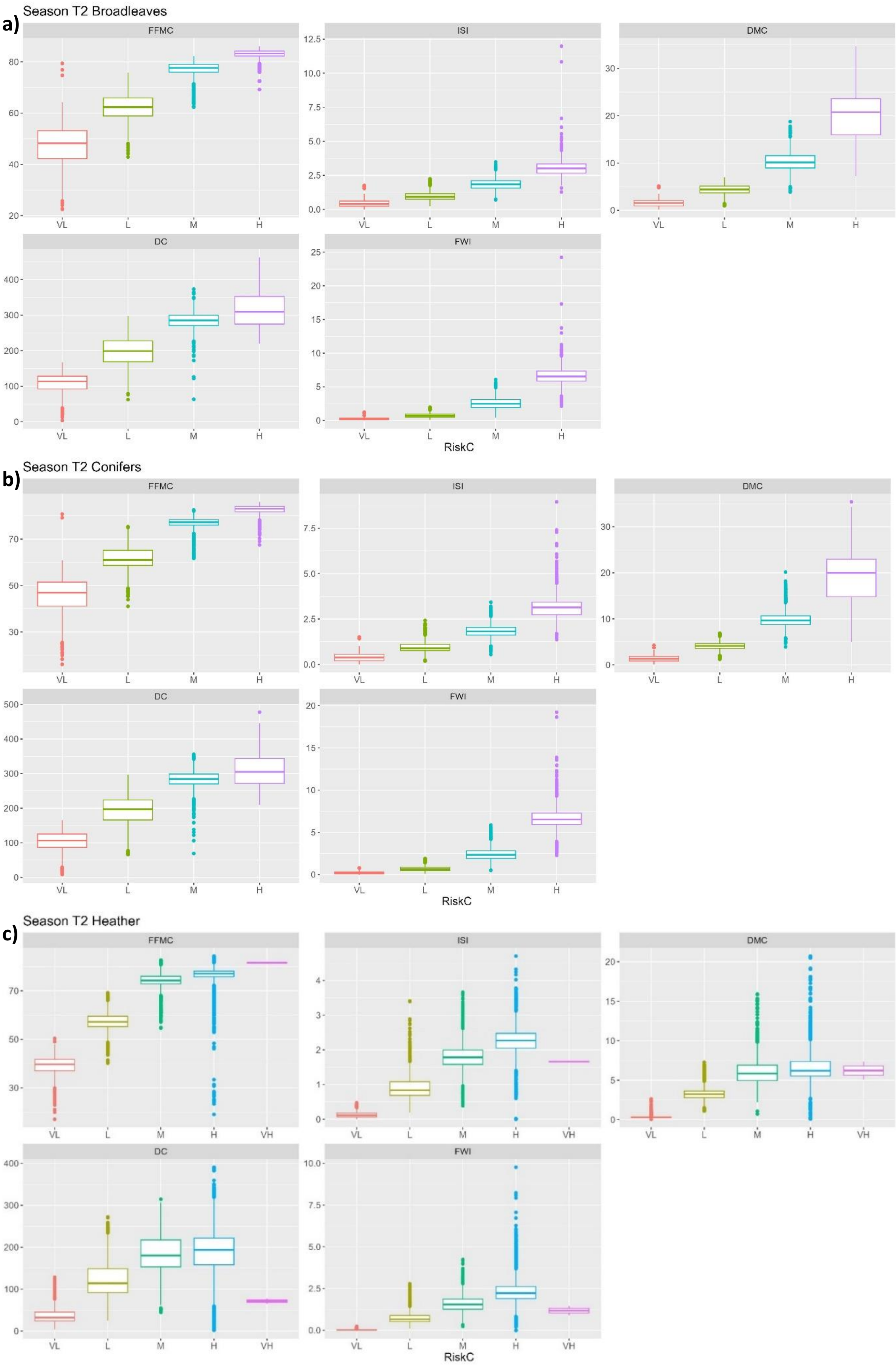


Figure 16. Map of a) Proportions (%) of Season T2 days within the Moderate Fire Danger Class and b) Fuel Type of areas falling within the Moderate or High Danger Class for >10% of Season T2 days, for the 2020-2049 period in the Cairngorms National Park.

There was little difference in elevation ranges in grid cells with Broadleaved and Conifers fuel types in both hotspot (Figures 19a and 19b) and all CNP grid cells (Appendix A2) between the Very Low, Low and Moderate Danger Classes, but High simulated fire danger generally occurred in lower altitudes. Elevation seemed to be a more important variable for distinguishing between low and high fire danger in areas on Heather, Bog and Seminatural Grasslands. As in Season T1, fire danger was found to increase with increasing FFMC and ISI for all fuel types (Figure 19 and Appendix A2), but with less clear distinctions for FFMC between danger classes in Heather areas. At the same time, DMC and to a lesser extent DC seemed to become more important in influencing fire danger in areas of Broadleaves, Conifers and Bogs, while FWI was identified as a driver of High fire danger for Broadleaves and Conifers, with n FWI being >5 in hotspot areas and ranging from 5.2 in August to 8.3 in August for the whole CNP area in days of simulated High fire danger in the 2020 - 2049 period.

Season T2 is outside the standard muirburn season in Scotland (October 1st to April 15th), so muirburns are not considered a potential ignition source in this period. However, Season T2 is the top touristic period in the Cairngorms, and the identified fire danger hotspots are easily accessible via local roads and path networks and in close proximity to most main touristic areas along the Spey and Dee rivers. Pressure from tourism and increasing visitor numbers can increase the likelihood of accidental ignitions and hence increase fire danger and risk in the identified hotspot areas.


a)
Season T2 Broadleaves
FFMC
ISI
DMC
DC
FWI
VL
L
M
H
RiskC
b)
Season T2 Conifers
FFMC
ISI
DMC
DC
FWI
VL
L
M
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c)
Season T2 Heather
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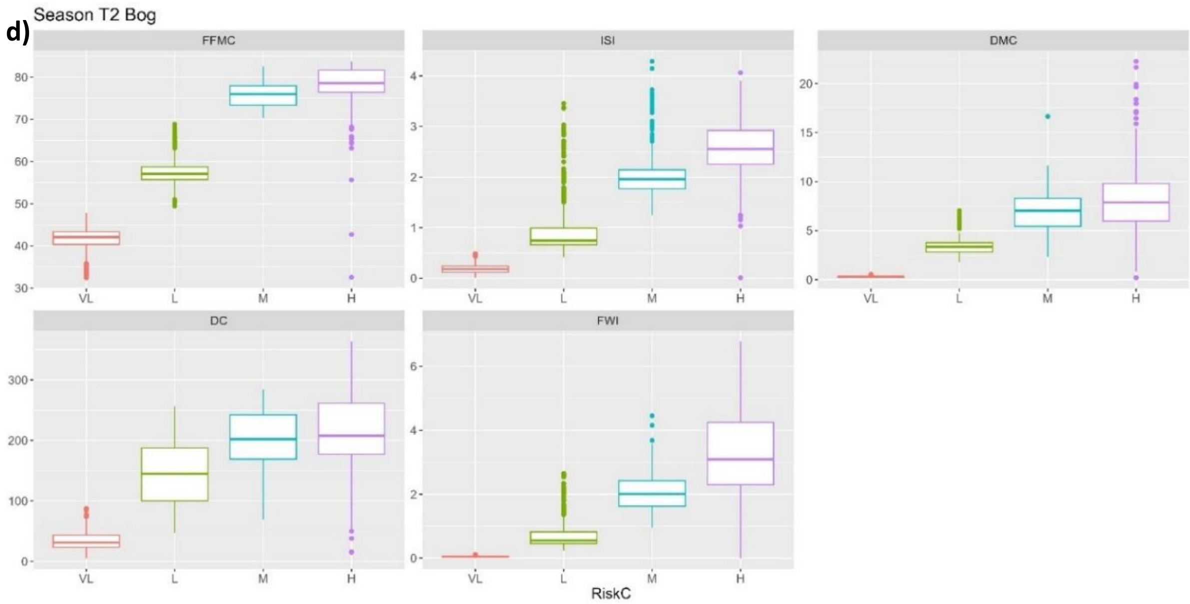

Figure 19. Boxplots of calculated Season T2 daily Fire Weather Index values by predicted Fire Danger classes for a) Broadleaves b) Conifers c) Heather and b) Bog areas in the Cairngorms National Park.

Season T3 Fire Danger Assessment

There was a further, substantial increase of hotspot areas, i.e., >10% days falling within the Moderate or High fire danger class in Season T3, which covers the period from October to December. Overall, 8,076 250m grid cells were identified as fire danger hotspots, covering an area of ~504 km^2 or 13% of the study area, with ~ 10% of these grid cells having >20% or >6 days a month on average falling within the Moderate Fire Danger class (Figure 20a). In addition, 436 grid cells (~27 km^2) were found to have >10% days falling within the High fire danger class. Regarding fuel type, ~84% of the fire danger hotspot area was covered by Heather, with almost all of the remaining area being covered by Bogs (~14%) (Figure 20b). The identified fire danger hotspots were located in four main areas: a) the area north and northwest to Grantown on-Spey, especially the hills north of Dulnain Bridge where most of this area had >20% days falling within the Moderate or >10% falling within the High Fire Danger class; b) the area between Strathspey to the west, Strath Avon, Hills of Cromdale and Auchnarrow to the east; c) the northern hillslopes of the river Dee from around Dinnet to the east to Braemar to the west, including the hills in Glen Gairn and the south-facing hills between Ballater and Easter Balmoral, and d) the west-facing hillslopes of the river Spey between Newtonmore and Kingussie and around the Coylumbridge area. Most of the fire danger hotspot area was covered by peaty podzols and peaty gleys (HOST15, 37%), followed by upland blanket peat (HOST29, 31%) and upland mineral soils such as humus-iron podzols (HOST17, 11%). Also, 60% of this area was located in Remote Rural Areas based on the Urban Rural classification (Fold=7) and 39% in Very Remote Rural Areas (Fold=8). Around 60% to 65% of all Season T3 days in the 2020 - 2049 period with Moderate or High fire danger occurred in October, followed by 28% and 37% in November for Moderate and High fire danger, respectively.

As previously, fire danger increased as elevation decreased in hotspot areas and for the whole CNP areas as well that were covered by Heather and Bogs (Figure 21 and Appendix A2), but elevation's effect was more prominent in distinguishing between low and high fire danger in areas covered by Bogs, where mean elevation in areas with simulated Moderate or High simulated fire danger ranged from 366m to 706m, while for Very Low and Low fire danger mean elevation ranged from 592m to 733m. Fire weather, especially FFMC and DC, seemed to be a more important driver of fire danger predictions than elevation or slope in areas covered by both Heather and Bogs (Figure 21). In the identified fire danger hotspot areas, mean FFMC in areas covered by Heather and Bogs was 64 to 68 for Moderate to High fire danger, compared to 37 and 44 for Very Low and Low fire danger. Interestingly, the 5th percentile values of FFMC in hotspot areas covered by Bogs and Heather were much higher for Moderate to High fire danger (36-53) compared to Very Low to Low fire danger (14-17), indicating little overlap between fire danger classes and low levels of confusion. These FFMC thresholds for both fuel types were also very similar for all fire danger classes to when the whole CNP area was assessed (Appendix A2). DC, which represents moisture at deep, organic layers, seemed to be a more important driver of fire danger than FFMC. 5th percentile, mean and 95th percentile values in Bog areas with Moderate to High fire danger was 58 and 136, 193 and 212 and 326 and 292, respectively, compared to 0.7 and 2.5, 17 and 94, and 63 and 237 for Very Low and Low fire danger, respectively. As with FFMC, these DC thresholds were similar when the whole CNP area was assessed. Similarly, for hotspots covered by Heather, 5th percentile, mean and 95th percentile values in Bog areas with Moderate to High fire danger was 72 and 145, 198 and 234 and 319 and 316, respectively, compared to just 0.9 and 3, 17 and 97, and 64 and 230 for Very Low and Low fire danger, respectively. Again, these thresholds were when the whole CNP area was assessed.

It has to be noted, that only 10 ignition/fire training samples were available for Season T2, extracted from only three burnt areas with Heather in eastern Scotland with fire dates in October 2018. This was because fires in late autumn and early winter are rare in the historical database. However, as demonstrated by the fire danger simulations, the model has the capacity to extrapolate and identify sensible patterns for under-represented combinations of fuel types and fire seasons. The calculated fire weather indices and simulated fire danger indicate an increase in the frequency of dry days and warmer conditions in late autumn and early winter in the study area. It is possible that the extent of the fire danger hotspot areas for Season T3 is overestimated due to the small number of samples used, however the model results strongly indicate a trend of increasing fire danger in the CNP for the 2020 -2049 period. In addition, combining the identified fire danger hotspots and mapped muirburn areas revealed their extensive spatial co-occurrence, with 76% and 65% of hotspot areas covered by Heather and Bogs, respectively, located in areas where muirburn is expected to occur. Season T3 is within the standard muirburn season in Scotland (October 1st to April 15th), so muirburns can be considered as a potential ignition source in this period that might further increase fire danger and fire risk in the study area in the future.

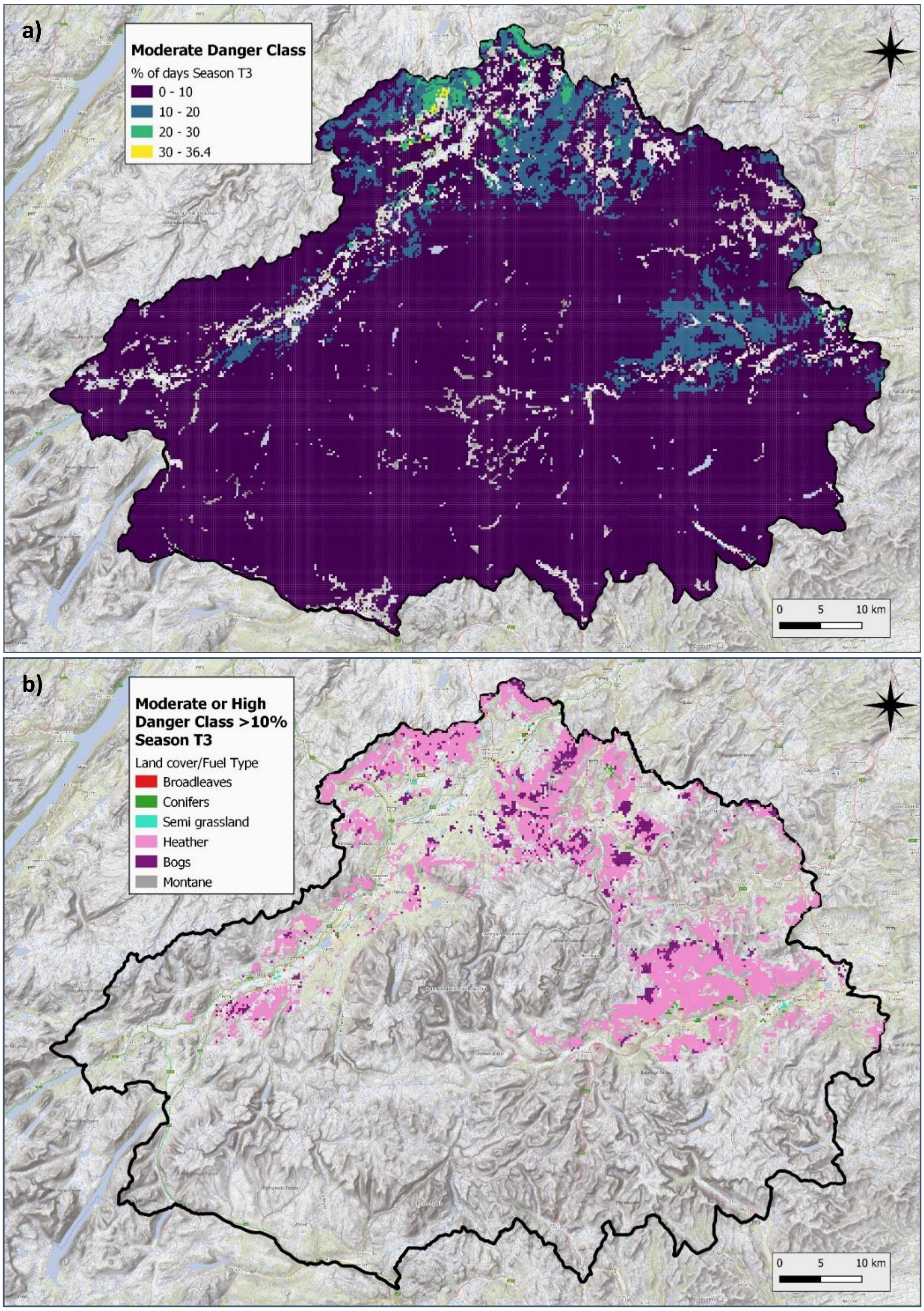

Figure 20. Map of a) Proportions (%) of Season T3 days within the Moderate Fire Danger Class and b) Fuel Type of areas falling within the Moderate or High Danger Class for >10% of Season T3 days, for the 2020-2049 period in the Cairngorms National Park.

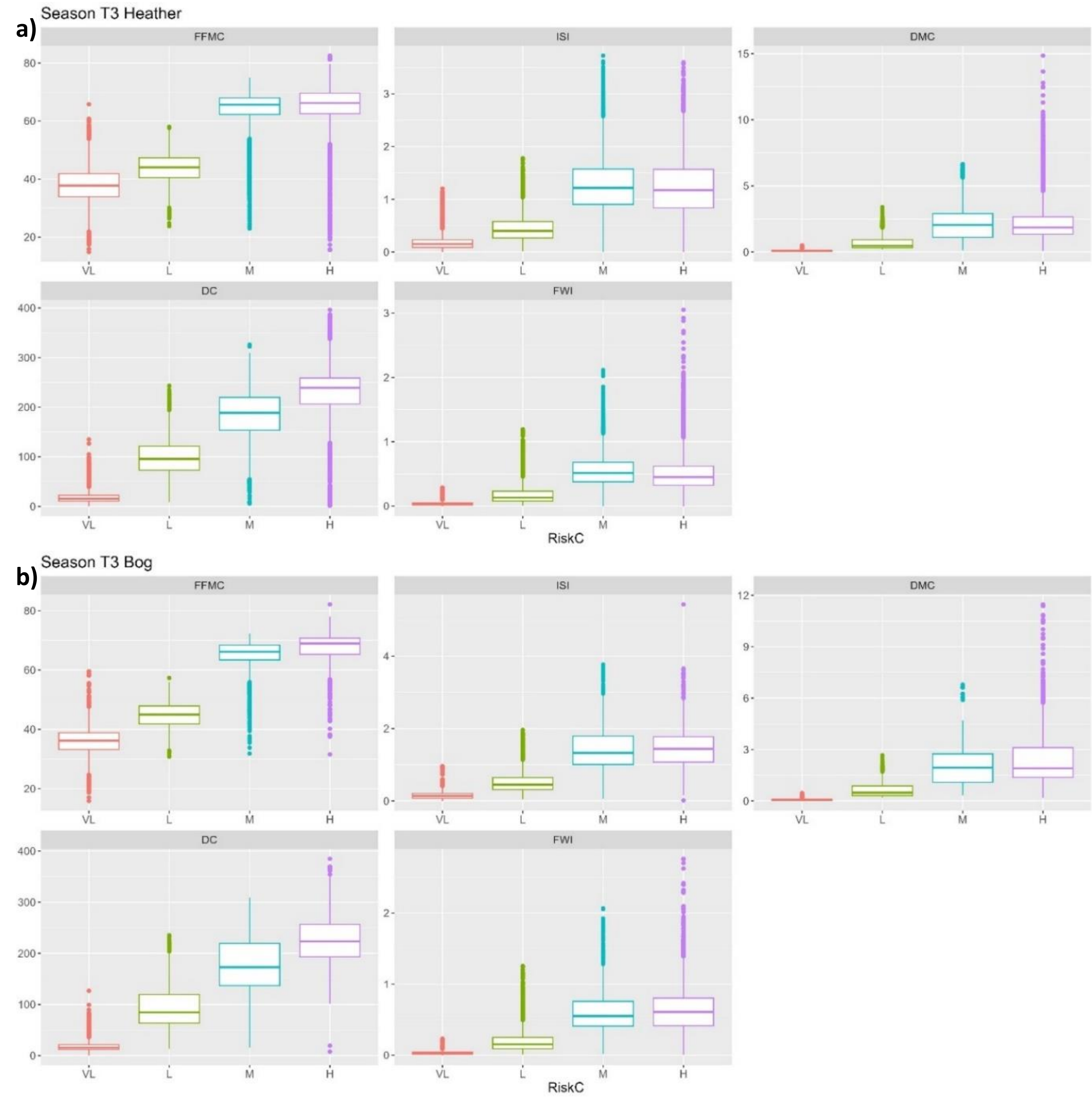

Figure 21. Boxplots of calculated Season T3 daily Fire Weather Index values by predicted Fire Danger classes for a) Heather and b) Bog areas in the Cairngorms National Park.

Independent model validation

Further model accuracy assessment to the one conducted via internal model validation using left-out samples (i.e., not used for model training) can be done using external model validation by simulating fire occurrence probabilities in new burnt areas that were not used for model training. This type of validation requires access to daily time-series (up to 2 months prior to the fire date) of climatic variables required for calculating the fire weather codes/indices from the meteorological stations nearest to the fire, and collation of the necessary spatial data layers described in Table 2. To demonstrate how this approach can be used for external accuracy assessment of the fire danger model, we simulated probabilities of fire occurrence for the recent (early April 2025) fire in Glen Trool in Galloway (Figure 22). This fire occurred during a warm and dry spell that lasted for almost two weeks in April 2025, and, according to EFFIS, burned 6,249 ha of mainly moorland vegetation, along with patches of conifer forestry at the burnt area perimeter. Climatic variables for fire weather code calculation were not available, so we relied on indicative values extracted from the EEFIS fire danger forecast system[5] for the specific date of fire initiation (April 4th 2025), calculated based on the ECMWF numerical weather forecast model (8 km resolution). EFFIS classifies fire weather code values based on thresholds common to the whole area of application (currently Europe, Middle East and North Africa) so we could only extract indicative and not actual values for the Glen Trool fire. However, with the exception of FFMC and ISI, these danger classes are based on thresholds that are not appropriate for Scottish conditions. Based on this source, FFMC was High (86.1 – 89.2), ISI was Very High (7.5 – 13.4), DMC was Low (<15.7), DC was Low (<256) and FWI was Low (<11.2). The FFMC and ISI classes were considered sensible and indicated the prevalence of warm and dry and windy conditions, and hence we used the lower limits (FFMC=86.1 and ISI=7.5). However, for the DMC, DC and FWI classes we used our expert opinion and used DMC=8, DC=125 and FWI=3. We also used a value of 15°C for daily temperature based on the average forecasted value from the Met Office website and assumed that no rainfall had occurred that day. Remaining covariate values for the burnt area were extracted from the land cover, terrain, soil, urban classification and region data layers, harmonised at 50m grid cell resolution, and along with the fire weather and temperature and precipitation values for the whole of the burnt area were inputted in the model and probabilities of fire occurrence were generated.

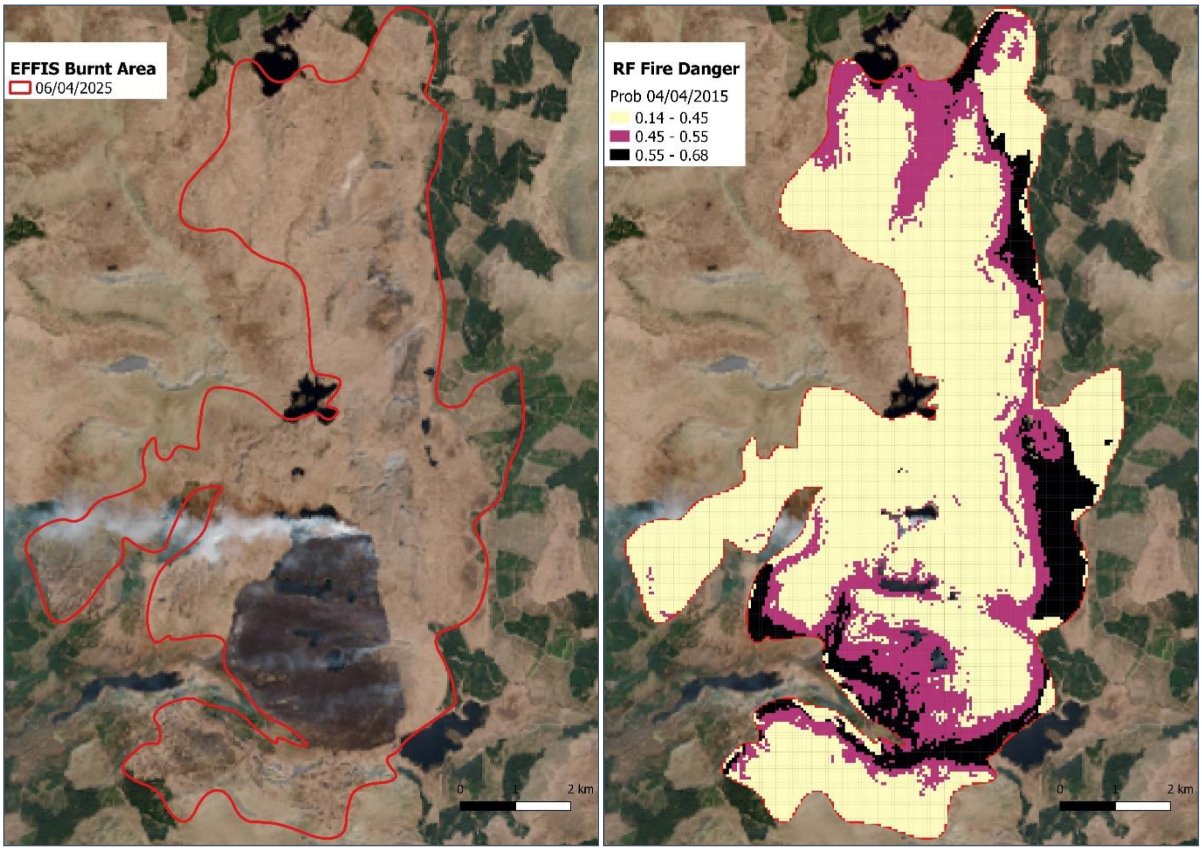

Figure 22. a) Burn scar of the Glen Trool fire on the day of fire initiation (April 4th 2025) (background satellite imagery from Copernicus browser[6]) and boundary of burnt area delineated by EFFIS (April 6th 2025) and b) probabilities of simulated fire danger on the day of fire initiation.

[5] https://forest-fire.emergency.copernicus.eu/apps/effis_current_situation/index.html
[6] https://browser.dataspace.copernicus.eu/

Figure 22a shows the burn scar while the fire was active on April 4th 2025 and Figure 20b gives the simulated fire danger probabilities for that date within the boundary of the total burnt area. We are unaware of the exact point of ignition, but it is certain that it is located within the burn scar area on the initiation date. Visual inspection of these two figures reveals that the model predicted Moderate to High fire danger within the burn scar where fire propagation occurred. The model also identified other areas of high danger but based on OS maps, these were less accessible than the area covered by the burn scar, which might explain the presence of an ignition source in that area. Therefore, despite the use of indicative (but sensible) fire weather and climate values, this assessment shows that the model performed well in predicting hotspots of fire danger in the Glen Trool fire area. Depending on data availability, conducting more of these external validation exercises could be used for providing more confidence on the accuracy of the fire danger simulations.

Limitations & potential Improvements

The probabilistic model developed in this study has been found to be performing well for conducting large scale spatial assessments and for identifying hotspots of fire danger. However, as with any ML-based approach, the model's accuracy depends on the overall quality of the dataset used to train the model, in terms of the use of an appropriate sampling design, the selection of informative and relevant covariates/predictors, and adequate representation of conditions or processes affecting the dependent variable being modelled. The training dataset developed in this study had two main limitations, that may have affected the model's predictive performance:

- Temporal imbalance: Seasonality is an important factor of fire danger dynamics, both due to differences in phenological characteristics of fuel types and the presence of different ignition sources in different seasons (e.g., pressures from tourism in summer months). However, most of the historical fires/burnt areas used to guide the generation of the train and test samples occurred in Season T1 (~70% of train samples) and most on Heather, while there were no samples from fires in August and September and only 10 ignition samples in late autumn, again only on Heather (Table A1, Appendix). As mentioned above, the model has produced sensible extrapolations for different fuel types in different seasons, but conducting more external validation in the future would provide further confidence in the model's predictions.
- Lack of recorded ignition points: Scotland is lacking a systematic way of recording wildfire ignition locations. In previous work (Gagkas et al., 2021) we have concluded that the SFRS Fire Incident Recording System (IRS), although containing valuable information that could be used to identify wildfire incidents with some certainty, was not fit for purpose for establishing a systematic record of historical wildfires and their characteristics, and provided recommendations to the SFRS on how the IRS could be improved for wildfire recording purposes. Hence, we used the alternative approach of drawing random samples within known burnt areas. This approach is both valid and appropriate for this type of modelling, but it is agnostic to the actual location of ignition, which hinders the use of more direct predictors of accessibility, such as distance to nearest paths and roads, that have been shown to be important for driving the likelihood of ignition. The use of elevation in this study served as an appropriate proxy for accessibility in most cases, and visual examination of mapped fire danger classes in the CNP showed that most identified hotspots were in proximity to paths and road networks, but being able to use calculated distances might have improved model predictions. Also, the modelling approach relied on the generation of non-ignition points and the presence of clear differences in covariate values between ignition and non-ignition sample points. It is possible

that the randomness of the sampling used, although appropriate for this modelling approach, could have added more confusion in the training dataset, that might have impacted the model's predictive performance. On the other hand, balancing the number of ignition and non-ignition samples by fire date should have improved the representativeness in the train dataset of fire weather conditions that drive fire danger in Scotland, and should have helped with the detection of patterns in fire weather code values by the algorithm.

- Use of CFWIS indices: Results showed that the CWFIS codes and indices were informative covariates, and fire danger predictions confirmed the presence of established relationships, e.g., the combined effect of FFMC and ISI on fire propagation in heather moorlands in late winter and spring and the importance of FWI for forest summer fires, but also highlighted the importance of other indices, e.g., DC, for driving fire danger in late autumn in heather moorlands and bogs. However, as mentioned before, these indices have not been developed for Scottish conditions and are not expected to always work relatively well in all fuel type conditions. The reason for using the CFWIS approach is that Scotland, and the UK, lacks an effective Fire Danger Rating System (FDRS) that can be used to predict wildfire risk and behaviour. Work by Taylor et al. (2021) has highlighted the importance of developing and validating a landscape-scale Scottish FDRS, tailored towards current land use change dynamics, such new woodland planting and natural tree regeneration. The main aims of a Scottish FDRS would be to characterise fuel loads (biomass) and field characteristics across representative geographic and phenologically diverse vegetation types; determine the flammability of different plant materials and structures under a range of climatic and moisture conditions both in the field and laboratory; and develop and validate predictive models by statistically relating climatic/weather variables to relevant fuel moisture contents, fuel flammability and fire behaviours that could be used to devise fire danger rating classes for fire danger forecasting and prevention planning. This statistical model could replace the use of CWFIS indices for representing fuel moisture contents and could potentially improve fire danger predictions made by models as the one developed in this study. Remote sensing technologies, along with assessment of moisture conditions both in the field and laboratory, can be utilised to build these new predictive models; a number of vegetation indices can be calculated from high resolution satellite imagery that can be used to map the spatial variation of vegetation and (top)soil moisture dynamics. These can be statistically related to a number of mapped climatic indices as the ones calculated by Rivington and Jabloun (2023), for example number of Consecutive Dry Days, that would allow predicting fuel moisture and its influence of fire danger both in the short-term (using weather forecasts) and long-term (using climatic projections) future.
- Resolution issues: Model predictions and resulting spatial assessments are influenced by the spatial scale or resolution of data layers used for developing the training dataset and spatially deploying model predictions, respectively. In this study, the scale and resolution of these data layers was appropriate for large scale mapping assessments, mainly for screening purposes such as identifying potential hotspot areas of fire danger. Simulating fire danger at a landscape scale, which could be of more interest to local authorities and land managers for fire prevention purposes, would require models trained at higher resolution to the one used in this study (e.g., 50m for terrain derivatives), and also deployed to finer resolution than the 250m pixel one used for the CNP. Obviously, this would substantially increase the modelling effort and computing resources required for running the models, especially if done at daily temporal and national spatial levels. On the other hand, the importance of variables known to influence fire

propagation, spread and severity, such as the terrain's aspect and slope (Naszarkowski et al., 2024), could become more prominent in landscape-scale modelling applications. It is also worth noting that land use/fuel type exerts a significant influence on the model simulations and consequently on the fire danger assessments. Uncertainties in the mapping of upland fuel types need to be resolved, especially between heather, heather grasslands and bogs in heather dominated moorlands and peatlands, to provide more accurate fire danger assessments. Also, high resolution vegetation mapping would be required if attempting to assess fire danger and risk of fire spread at landscape scale in ecosystems in transition such as in areas of woodland natural regeneration or areas where rewilding is actively promoted, to ensure that the mosaic of fuel types and their connectivity is adequately captured.

- Static fuel type mapping: Land cover/fuel type composition was held constant during model simulations, but major land use and management changes are planned in the CNP related, for example, to woodland expansion and peatland restoration. A further improvement to the modelling approach could be to feed temporally variable fuel type composition maps, based on scenarios as those used in Valette et al. (2023), into the model to generate coupled climate and land cover change spatial assessments of fire danger.
- Methods devised for fire danger assessments: This work produced daily simulations of fire occurrence probabilities for a 30-year period (10,800 days) for each of the 66,692 250m grid cells covering the extent of the CNP, resulting in more than 720 million individual data points. Hence, an important aspect of this job was to find a meaningful way of processing this big dataset to facilitate the generation of large scale, spatial assessments of fire danger. For this reason, we devised fire danger classes and calculated counts of days falling within these classes and their respective proportions for the three selected seasons and defined potential hotspots of future fire danger those areas with simulated fire danger being Moderate or High for more than 10% of the 2020 - 2049 period. We considered this approach to be sensible and appropriate for the purpose of this work because it provided "on average" fire danger conditions for the 30-year period studied. However, defining fire danger classes using different probability thresholds and/or detecting fire danger hotspots using different (lower or higher) proportion thresholds would have obviously resulted in different spatial assessments. Also, an alternative approach could have been to define hotspots by focusing on the number of consecutive (instead of total) days with Moderate and/or High fire danger or by selecting wet vs dry years within the 2020 - 2049 period to compare fire danger assessments based on contrasting climate scenarios, both spatially and temporally. It was not feasible to explore these different options in this work but depending on availability of resources these could be the focus of future work.

Conclusions

The main conclusions from this study are listed below:

- The ML-based, probabilistic modelling proved to be an appropriate approach for modelling fire danger at large scale and for conducting spatial assessments for identifying hotspots of future fire danger in the Cairngorms National Park for the 2020 - 2049 period, despite issues related to the representativeness of the training dataset developed and uncertainties related to land use/fuel type mapping.
- The combined use of CWFIS codes and indices showed good potential and some interesting patterns emerged from this analysis, but their calculation can be data intensive, and their

interpretation complicated, which highlights the need for developing fire weather indices specific to Scottish conditions.

- Hotspots of future fire danger varied by season but were mostly located at the northern and eastern areas of the CNP, and along the hillslopes of the Spey and Dee river valleys. Moderate to High future fire danger was found to be relatively limited in its extent in heather moorlands in the Park during the late winter to early spring period, which currently is the main fire season in Scotland when most of fire activity is recorded. This indicates changing climatic conditions within the CNP, with wetter conditions increasing the resilience to fire propagation. On the other hand, fire danger seemed to increase and be quite extensive in heather moorlands and peatlands during late autumn and early winter, indicating the prevalence (on average) of relatively dry weather conditions. Results showed that summer forest fires were quite probable for extensive areas of the CNP, especially in conifer plantations in the Spey and Dee valleys and adjacent hills. It is worth noting that these assessments are based on projections from only one plausible future scenario (EM01); use of different climate projections could change magnitudes of fire danger and related spatial patterns, but the data are seen[7] as being consistent with 11 other climate projections (ensemble members) and are representative of the possible direction of change in the CNP.
- Spatial co-occurrence of fire danger hotspots with recognised pressures within the CNP that can act as ignition sources could be of major concern in the short-term future. For example, hotspots of potential future forest fire activity were located within close proximity to road and path networks, and to major settlements that see their population densities and usage greatly increase during late spring and summer months due to the popularity of the Park as a touristic destination. At the same time, most of the heather moorland area identified as hotspots of fire danger in late autumn to early winter is located in land that is managed using prescribed burning. It is suggested that these findings, and their associated uncertainties, are taken into consideration for future fire prevention planning purposes.

Next Steps

Proposed next steps aim to further progress this work and integrate it in frameworks for the assessment of impacts on the condition and functions of selected NC assets. In particular, main actions include:

- Share the report and respective maps with the Cairngorms National Park Authority and request their feedback regarding the approach and results, e.g., explore how identified future hotspots of fire danger compare to the Authority's fire incident records and/or local knowledge.
- Continue work on developing methods for condition and functioning assessments for selected NC assets and for vulnerability assessments in relation to the threats of meteorological drought and fire.
- Explore ways to progress previous conceptual work towards developing a fire risk modelling framework by integrating the fire danger modelling work with condition and vulnerability assessments and D5-2 work on wildfire perceptions and mitigation strategies to be used for assessing fire impacts on the delivery of ecosystem services from selected NC assets.

[7] The James Hutton Institute Climate Data Visualisation

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Appendix

A1. Descriptive statistics of continuous covariates values by Season in the training dataset

A2. Boxplots of fire danger index, elevation and slope values by fire danger class and month for all 250 grid cells in the study area.

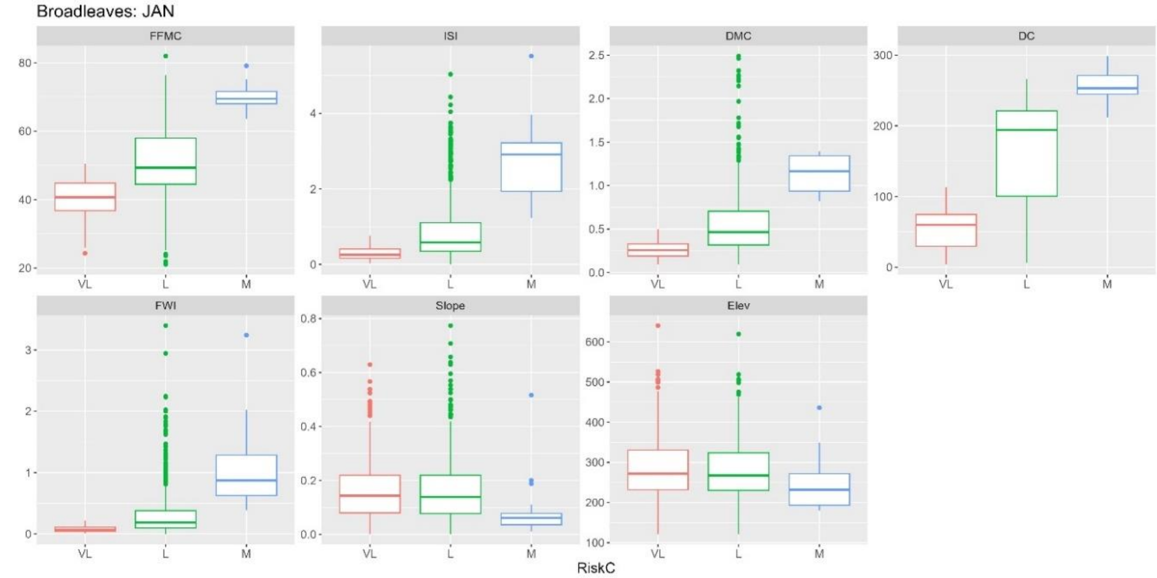
A1. Descriptive statistics of continuous covariates values by Season in the training dataset

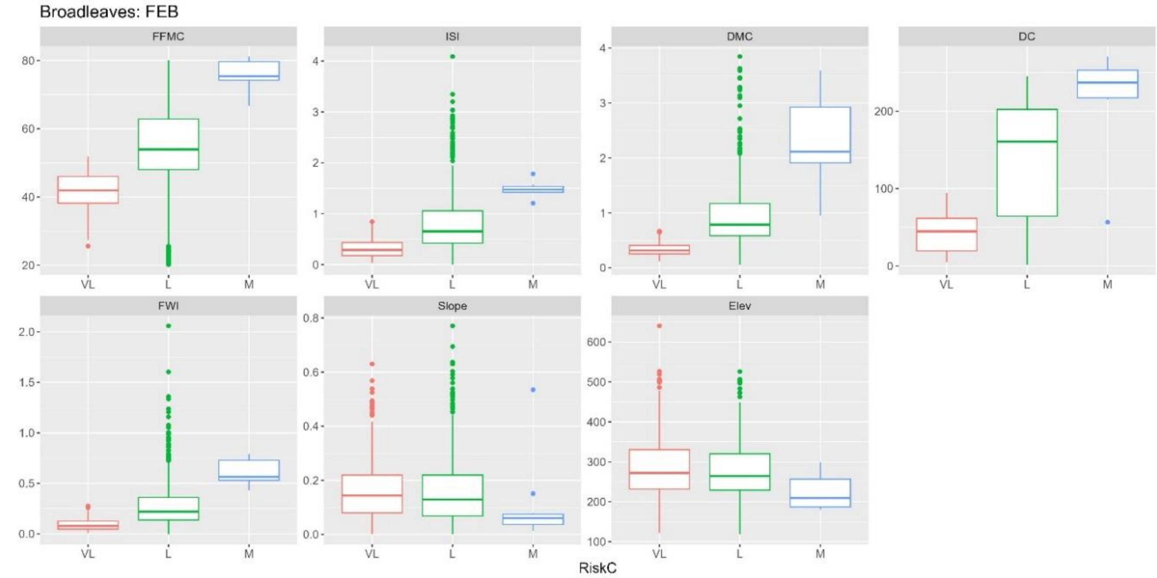
Land Cover/ Fuel Type	Fire	Season	Count	Temperature (°C)			Precipitation (mm)			FFMC			ISI			DMC		
				Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Broadleaves	Yes	T1	10	0.56	6.67	13.80	0.00	0.00	0.00	77.64	79.90	81.37	1.16	3.16	4.75	0.74	4.35	10.71
Broadleaves	No	T1	48	-3.94	6.27	14.61	0.00	0.76	8.64	19.92	72.28	81.74	0.00	1.95	8.23	0.00	3.76	12.60
Broadleaves	Yes	T2	8	9.07	10.83	15.19	0.00	0.00	0.00	79.97	81.02	82.30	1.85	2.08	2.38	5.62	9.72	12.62
Broadleaves	No	T2	15	7.38	10.62	15.47	0.00	0.07	1.01	59.29	77.64	82.51	0.51	2.31	4.27	2.23	9.36	18.12
Conifers	Yes	T1	23	-0.08	7.78	12.39	0.00	0.03	0.70	70.13	78.93	81.68	0.83	2.84	5.38	0.90	4.96	9.60
Conifers	No	T1	188	-4.57	5.19	14.89	0.00	1.19	35.31	20.78	69.93	81.94	0.00	1.98	8.97	0.00	3.03	10.97
Conifers	Yes	T2	22	7.83	11.49	16.94	0.00	0.04	0.49	71.98	79.90	82.07	1.11	2.70	4.15	2.31	11.43	24.60
Conifers	No	T2	65	5.62	10.64	15.83	0.00	0.38	13.85	38.29	79.24	82.95	0.06	2.74	4.84	1.37	9.46	23.94
Semi grassland	Yes	T1	22	0.55	7.21	13.92	0.00	0.01	0.20	73.41	77.84	80.75	1.16	2.19	4.92	0.74	3.41	7.22
Semi grassland	No	T1	82	-3.97	5.87	14.32	0.00	0.66	14.67	20.55	72.99	81.82	0.00	2.10	5.77	0.00	3.36	12.70
Semi grassland	Yes	T2	11	8.72	10.31	12.51	0.00	0.00	0.00	79.92	80.89	81.56	1.54	2.25	3.06	7.89	11.58	21.60
Semi grassland	No	T2	30	5.98	10.08	15.77	0.00	0.17	2.26	66.12	79.20	82.44	0.86	2.47	4.41	2.42	8.98	15.98
Heather	Yes	T1	499	-2.47	6.46	14.62	0.00	0.47	9.23	31.90	75.15	81.75	0.01	2.29	7.51	0.04	3.22	10.66
Heather	No	T1	339	-5.49	5.01	14.80	0.00	0.82	19.02	20.72	71.93	81.67	0.00	2.20	8.97	0.00	2.63	10.27
Heather	Yes	T2	215	4.90	10.56	16.41	0.00	0.02	0.49	62.20	79.20	82.29	0.76	2.18	4.32	2.40	7.35	21.77
Heather	No	T2	140	3.96	9.79	16.81	0.00	0.73	16.71	34.36	75.86	82.62	0.02	2.20	5.71	0.54	6.83	18.45
Heather	Yes	T3	10	1.64	5.32	8.85	0.00	0.33	0.85	51.20	64.36	75.34	0.54	1.18	2.30	0.50	1.42	2.50
Heather	No	T3	6	3.52	5.88	8.32	0.00	0.86	1.92	40.39	56.99	68.34	0.06	0.90	2.08	0.18	0.74	2.39
Bogs	Yes	T1	278	-3.63	4.42	12.72	0.00	0.19	18.68	24.87	77.36	81.00	0.00	3.45	8.19	0.11	2.70	9.00
Bogs	No	T1	124	-5.33	5.20	14.87	0.00	0.90	37.38	20.20	72.73	81.32	0.00	2.44	11.51	0.00	2.59	8.87
Bogs	Yes	T2	93	7.74	11.66	18.06	0.00	0.06	1.10	68.35	75.90	81.94	1.09	1.80	3.75	2.22	5.89	20.27
Bogs	No	T2	74	4.51	9.55	16.41	0.00	0.16	4.32	47.41	78.53	82.58	0.29	2.49	5.13	1.73	7.33	17.84
Montane	Yes	T1	13	2.90	6.50	11.35	0.00	0.00	0.00	77.79	79.21	80.92	1.12	3.21	8.20	1.99	3.30	5.54
Montane	No	T1	72	-6.61	2.97	13.64	0.00	0.87	17.50	27.20	71.91	81.10	0.00	2.77	14.98	0.00	1.49	6.87
Montane	Yes	T2	6	6.22	8.00	10.00	0.00	0.00	0.00	78.56	79.38	81.15	1.60	2.43	2.98	2.93	6.22	10.80
Montane	No	T2	31	1.18	7.62	15.14	0.00	1.07	16.86	29.87	75.29	82.42	0.01	2.65	5.17	0.39	5.31	12.81

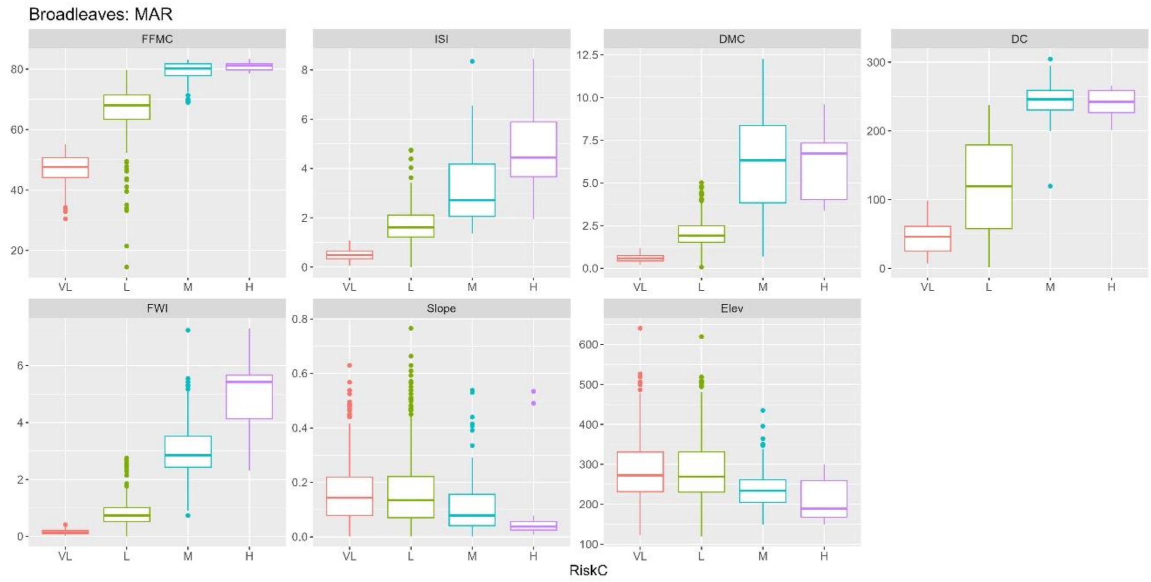
Land Cover/ Fuel Type	Fire	Season	Count	DC			FWI			Elevation (m)			Slope (radians)		
				Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Broadleaves	Yes	T1	10	1.07	24.42	55.01	0.36	2.50	5.60	57.10	130.43	244.30	0.15	0.45	0.72
Broadleaves	No	T1	48	0.00	20.35	59.40	0.00	1.25	4.64	4.00	106.17	300.60	0.01	0.17	0.63
Broadleaves	Yes	T2	8	36.09	55.96	80.41	1.87	2.36	3.56	38.20	99.15	214.60	0.20	0.38	0.62
Broadleaves	No	T2	15	42.32	81.18	168.06	0.21	3.02	6.62	38.20	143.63	348.40	0.02	0.21	0.44
Conifers	Yes	T1	23	2.62	28.95	58.80	0.24	2.26	6.04	99.40	254.36	348.90	0.01	0.11	0.34
Conifers	No	T1	188	0.00	17.91	174.19	0.00	1.26	7.05	5.30	212.75	500.60	0.00	0.15	0.65
Conifers	Yes	T2	22	32.58	138.91	337.05	0.49	4.09	7.15	45.50	167.30	281.90	0.00	0.07	0.22
Conifers	No	T2	65	5.92	70.61	169.69	0.02	3.47	7.33	12.60	234.64	488.50	0.01	0.14	0.41
Semi grassland	Yes	T1	22	0.38	20.12	42.97	0.35	1.12	3.92	47.10	159.73	420.40	0.03	0.22	0.64
Semi grassland	No	T1	82	0.00	21.19	168.48	0.00	1.31	5.92	0.00	170.89	457.40	0.00	0.16	0.66
Semi grassland	Yes	T2	11	41.18	82.98	225.13	1.51	3.04	5.71	32.00	139.91	318.90	0.04	0.26	0.56
Semi grassland	No	T2	30	23.60	71.85	178.33	0.35	3.03	5.94	6.70	228.79	395.30	0.00	0.16	0.54
Heather	Yes	T1	499	0.00	19.09	86.50	0.00	1.36	7.18	2.00	207.86	553.90	0.00	0.18	0.77
Heather	No	T1	339	0.00	15.42	53.94	0.00	1.28	7.45	15.90	329.08	790.00	0.01	0.21	0.85
Heather	Yes	T2	215	20.24	59.81	309.28	0.40	2.13	7.69	28.60	177.71	544.40	0.01	0.18	0.70
Heather	No	T2	140	3.50	65.17	282.33	0.01	2.27	7.43	14.50	327.24	697.20	0.01	0.22	0.85
Heather	Yes	T3	10	58.23	175.98	260.52	0.20	0.37	0.60	302.00	432.01	678.30	0.05	0.17	0.34
Heather	No	T3	6	3.07	104.54	265.51	0.01	0.25	0.51	136.70	330.62	596.40	0.08	0.25	0.35
Bogs	Yes	T1	278	0.14	15.52	59.24	0.00	1.89	7.14	4.20	189.43	576.50	0.00	0.09	0.41
Bogs	No	T1	124	0.00	16.23	56.76	0.00	1.43	8.34	8.00	309.82	798.80	0.00	0.09	0.64
Bogs	Yes	T2	93	21.29	82.03	288.09	0.49	1.52	6.14	54.70	151.14	540.50	0.00	0.06	0.38
Bogs	No	T2	74	13.96	65.38	225.24	0.13	2.60	6.89	14.00	344.35	798.80	0.01	0.10	0.29
Montane	Yes	T1	13	13.06	20.64	30.06	0.45	1.98	6.09	179.20	386.66	612.70	0.19	0.47	0.84
Montane	No	T1	72	0.00	10.67	38.35	0.00	1.33	10.70	201.70	683.59	1053.70	0.05	0.34	0.72
Montane	Yes	T2	6	23.11	43.75	61.03	0.94	2.08	3.23	360.90	513.63	627.70	0.15	0.60	0.95
Montane	No	T2	31	3.65	47.58	120.37	0.00	2.39	6.45	201.70	672.08	1165.80	0.05	0.29	0.51

A2. Boxplots of fire danger index, elevation and slope values by fire danger class and month for all 250 grid cells in the study area.

Broadleaves






Broadleaves: MAR
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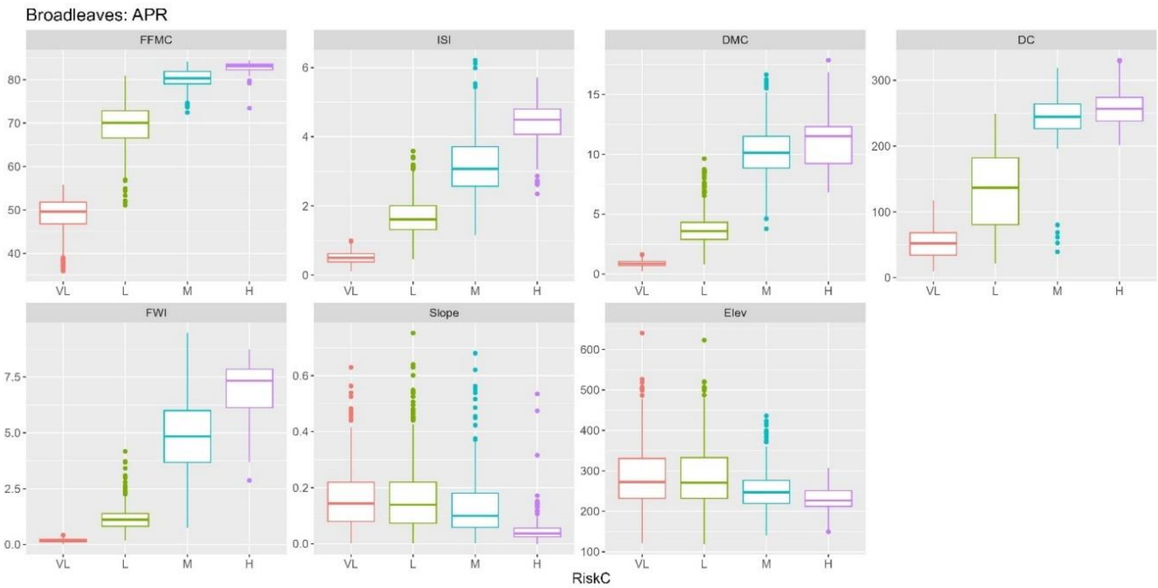
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC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DMC
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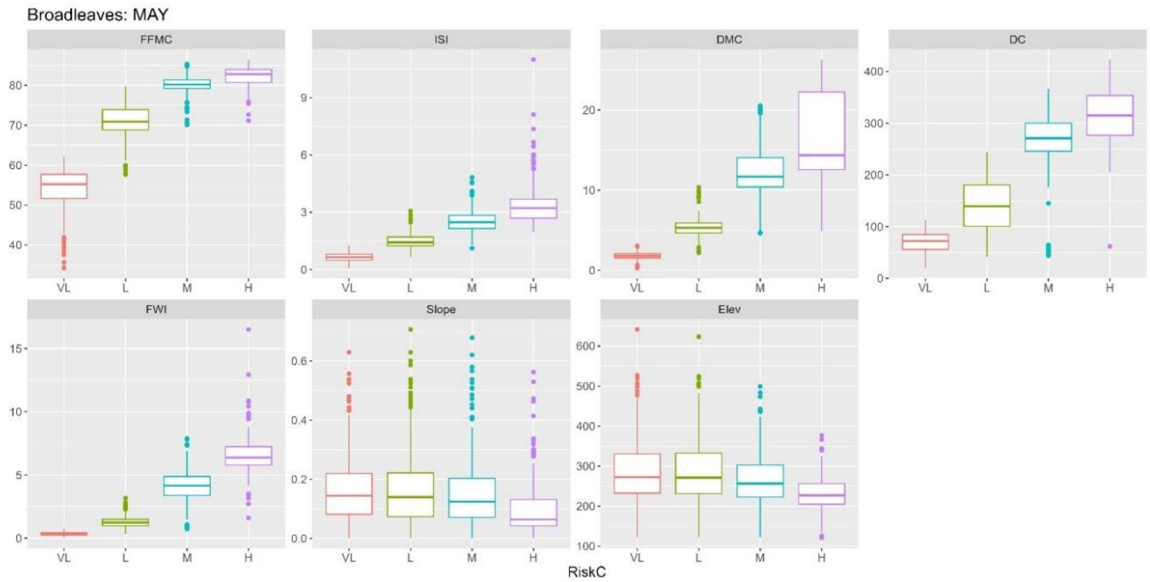
FWI
Slope
Elev
VL L M H
RiskC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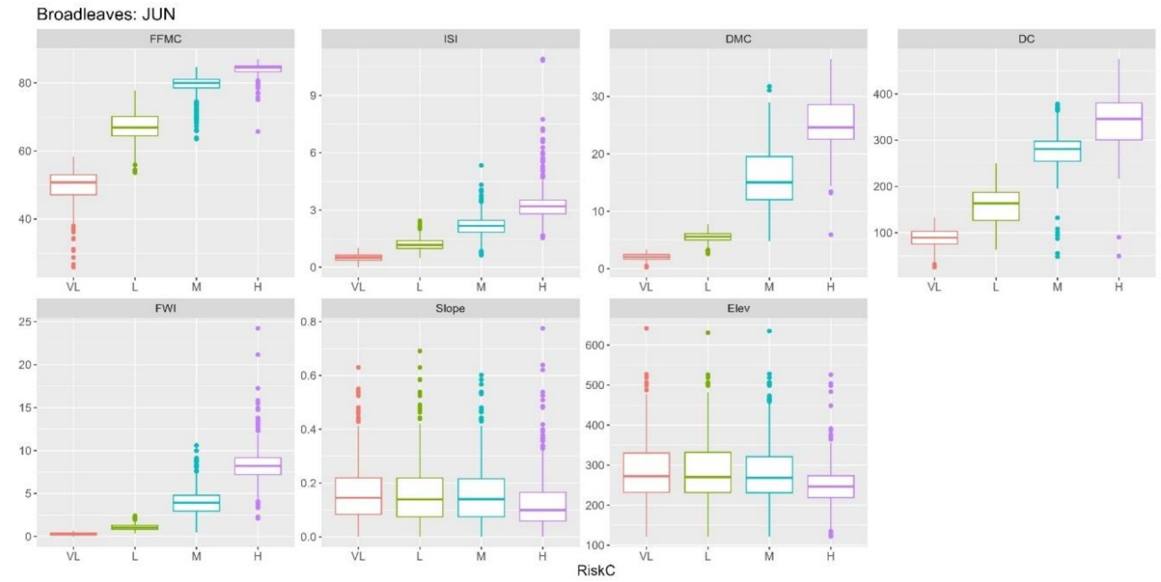
FWI
Slope
Elev
VL L M H
RiskC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DMC
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FWI
Slope
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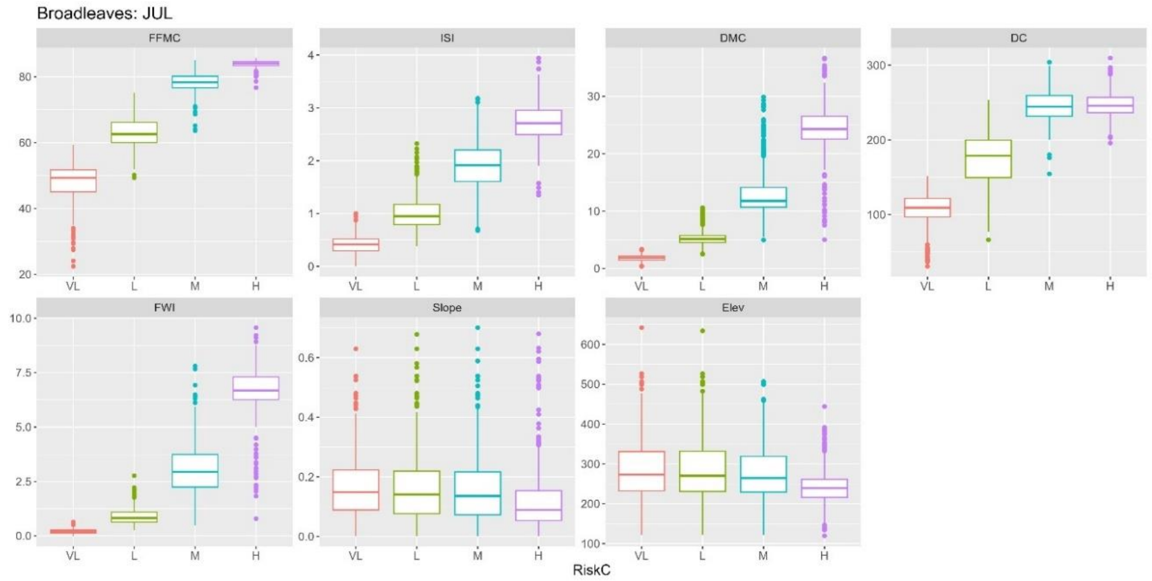
VL
L
M
H
RiskC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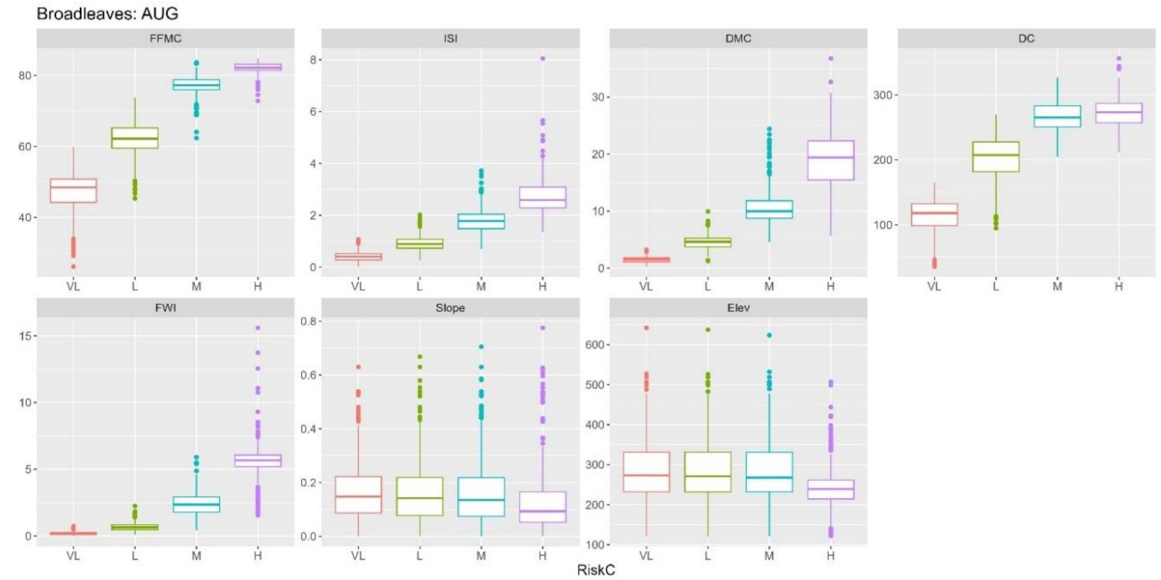
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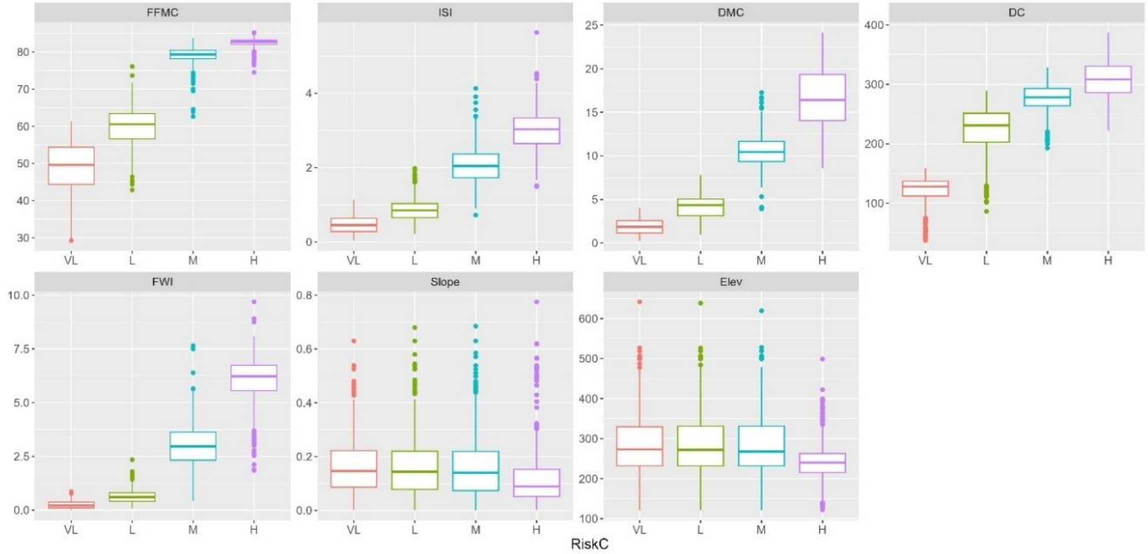
RiskC

Broadleaves: SEP



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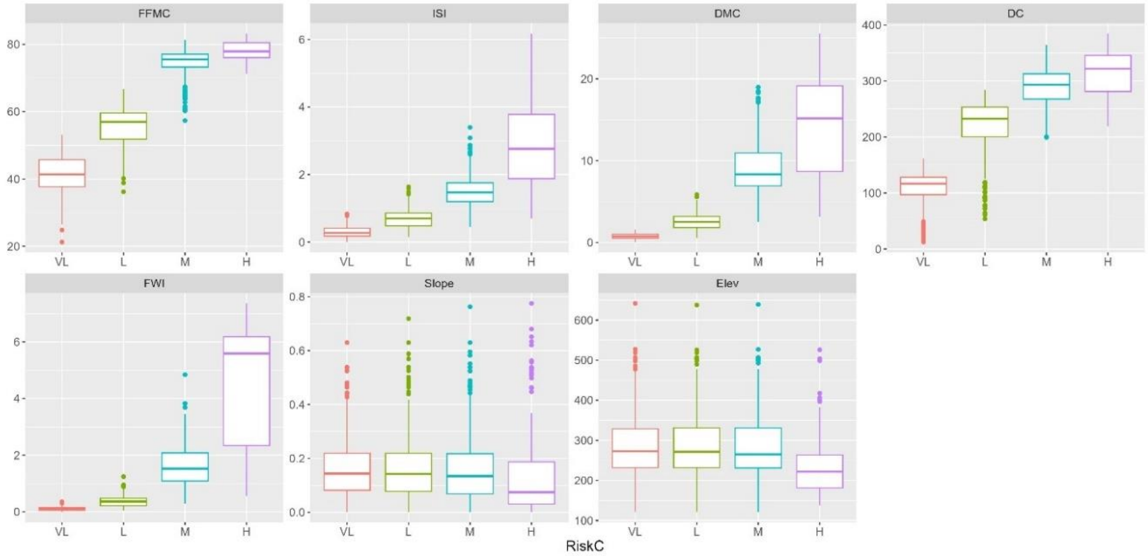

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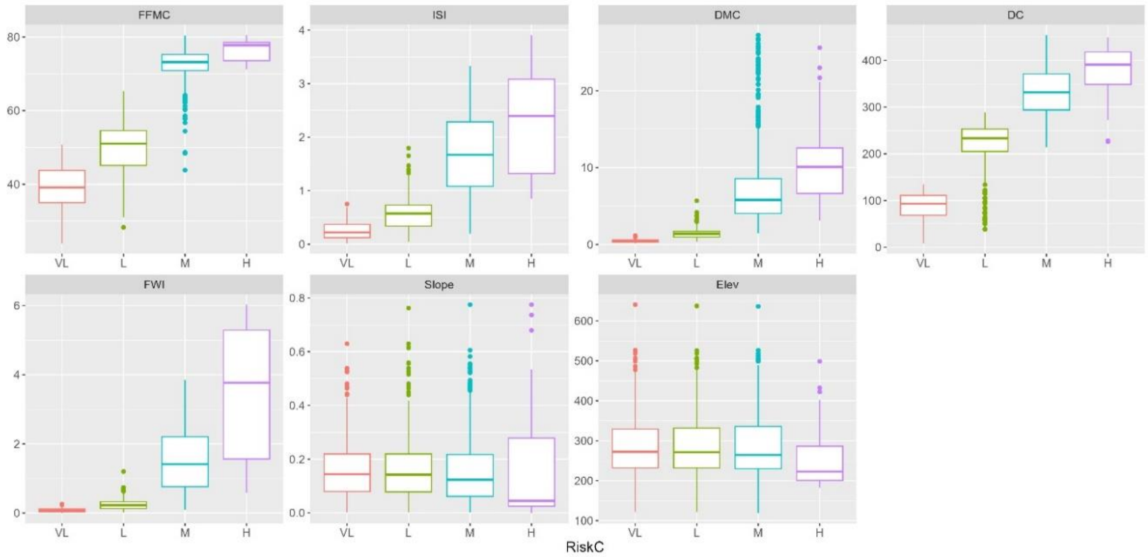

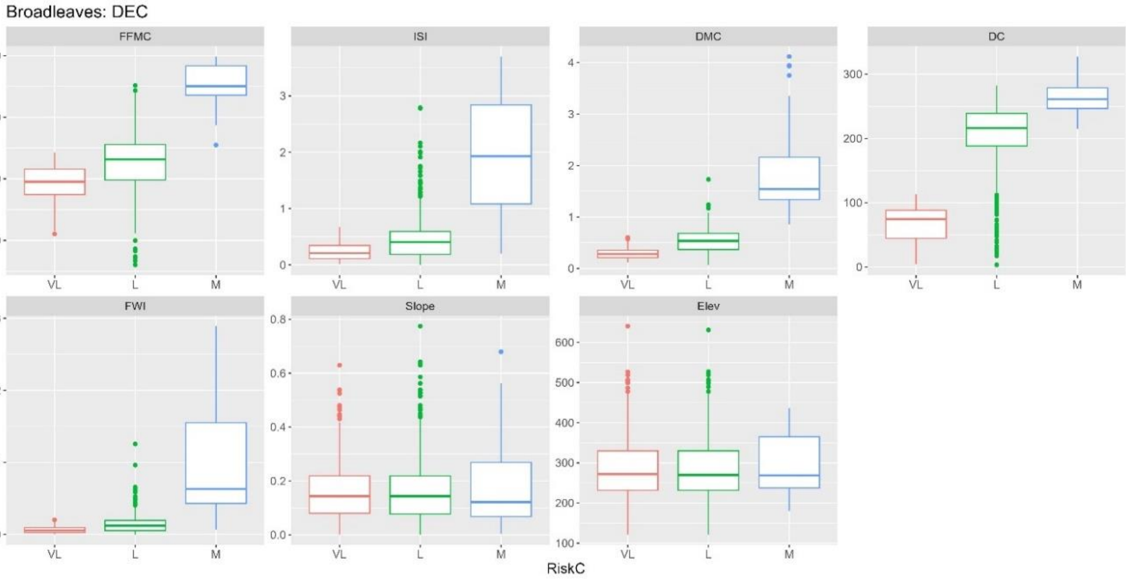
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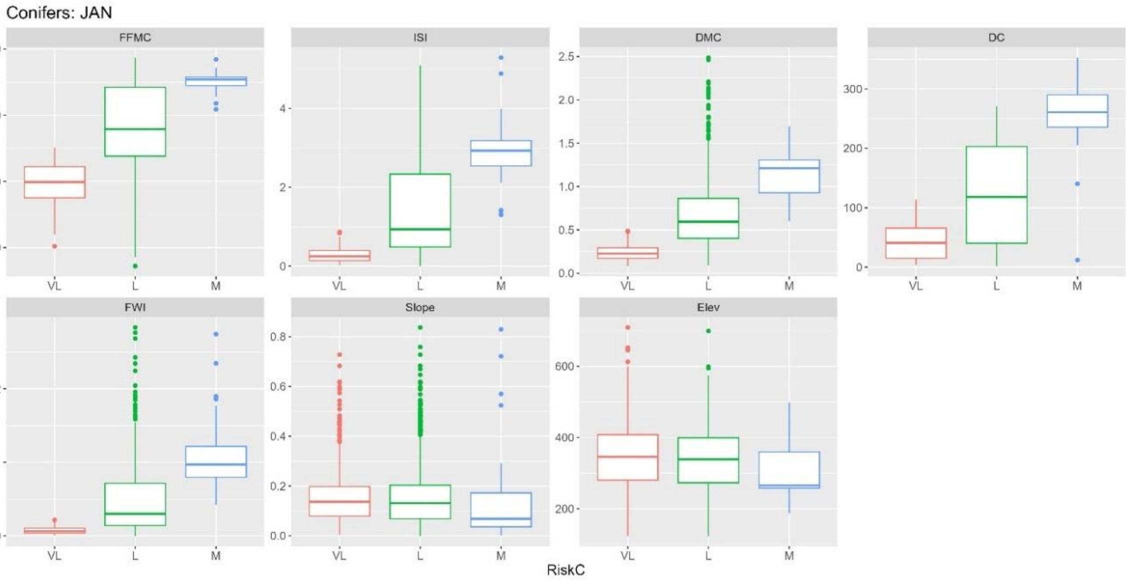
FWI
Slope
Elev
VL
L
M
RiskC

Conifers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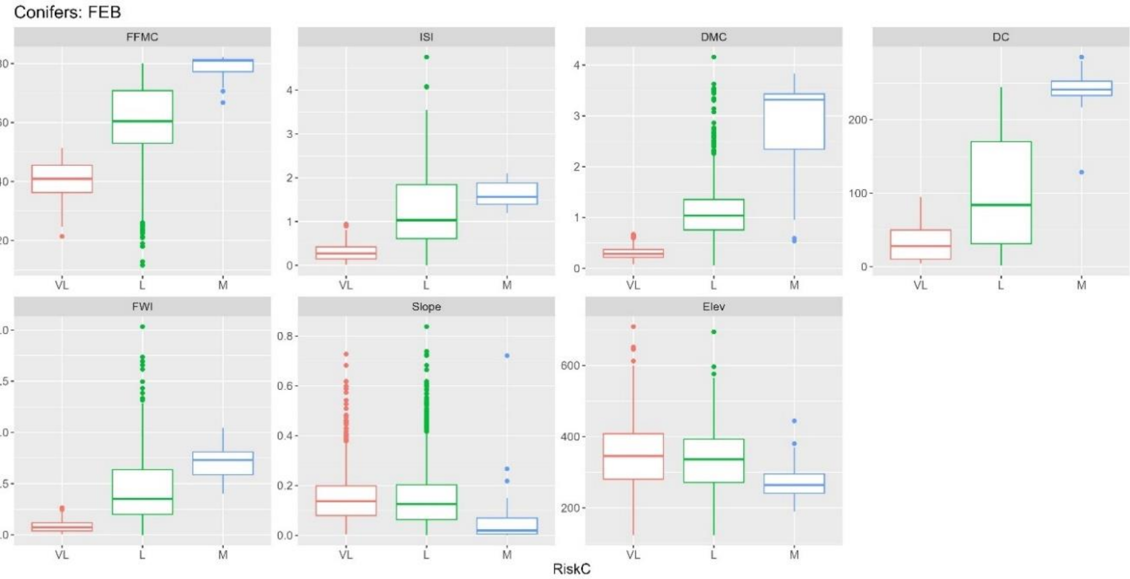
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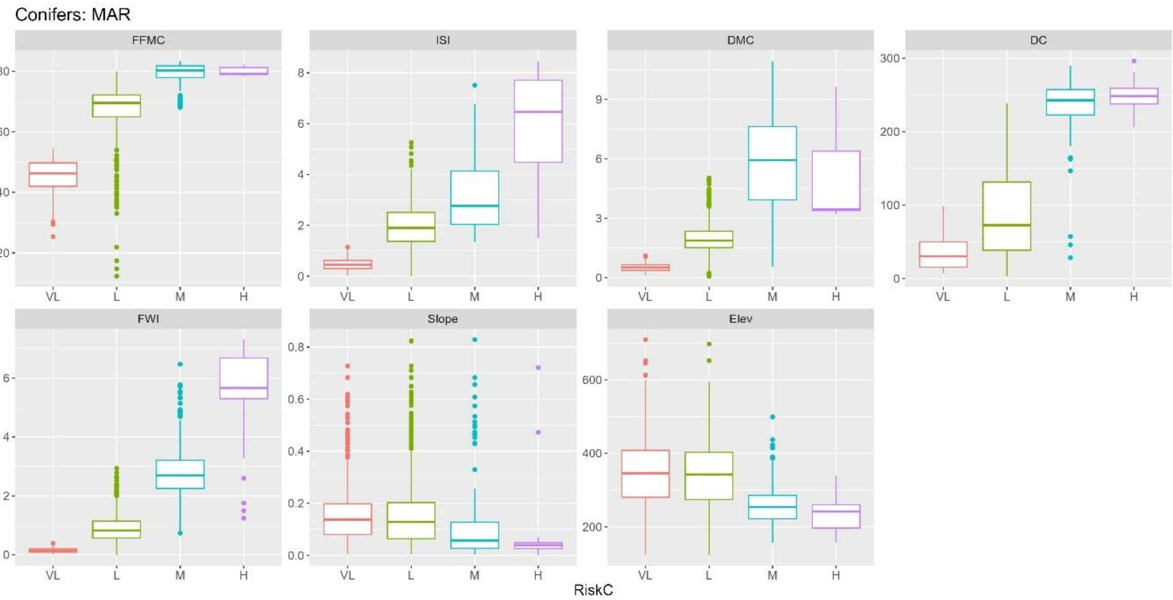
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VL L M H
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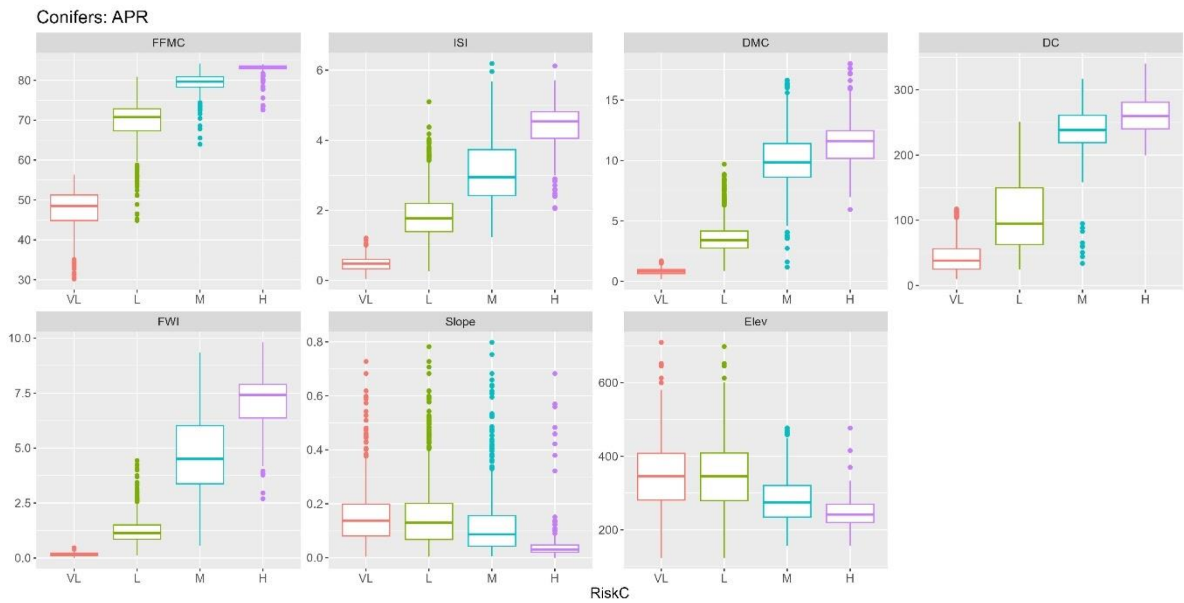
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DMC
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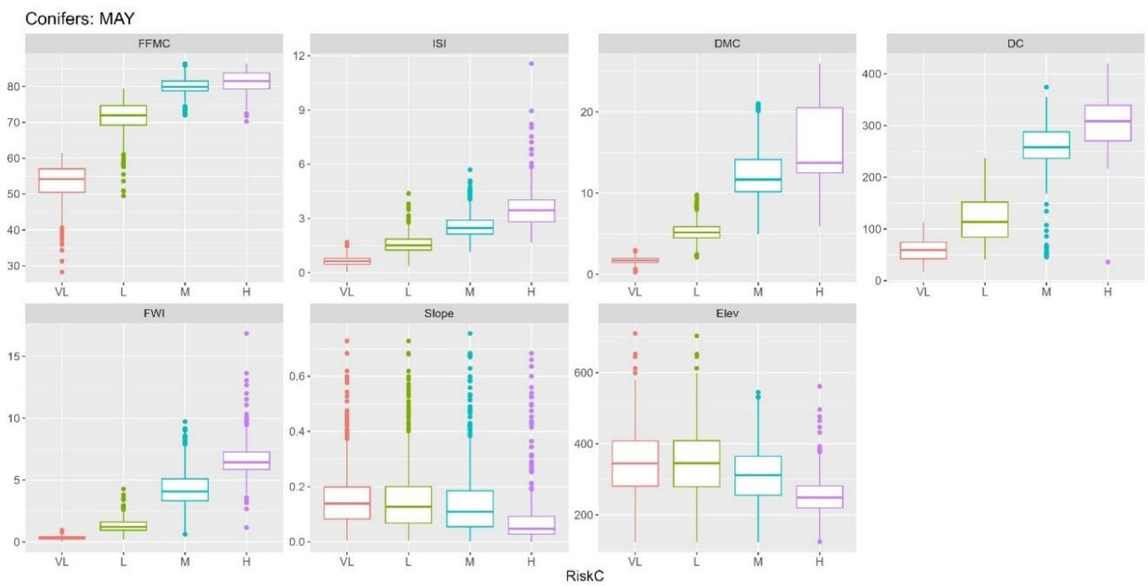
Elev
VL L M H
RiskC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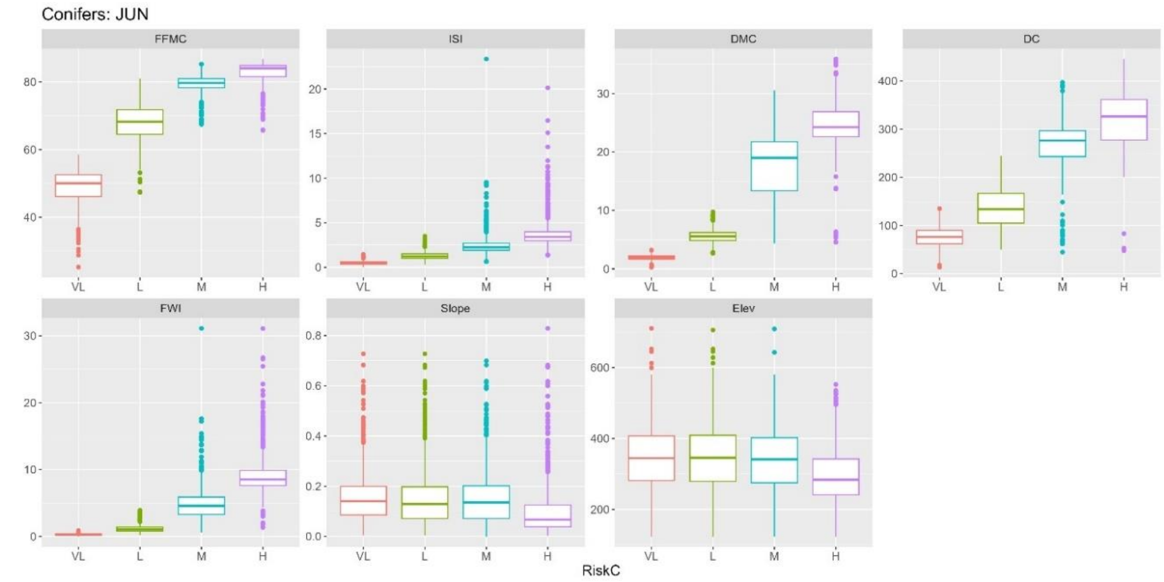
Elev
VL L M H
RiskC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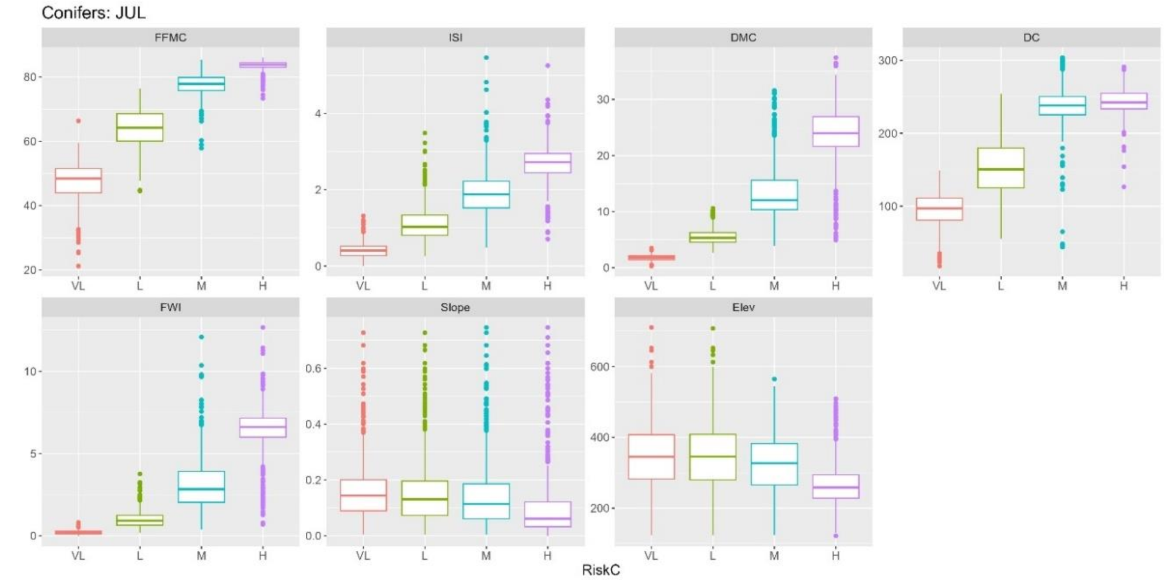
VL L M H
RiskC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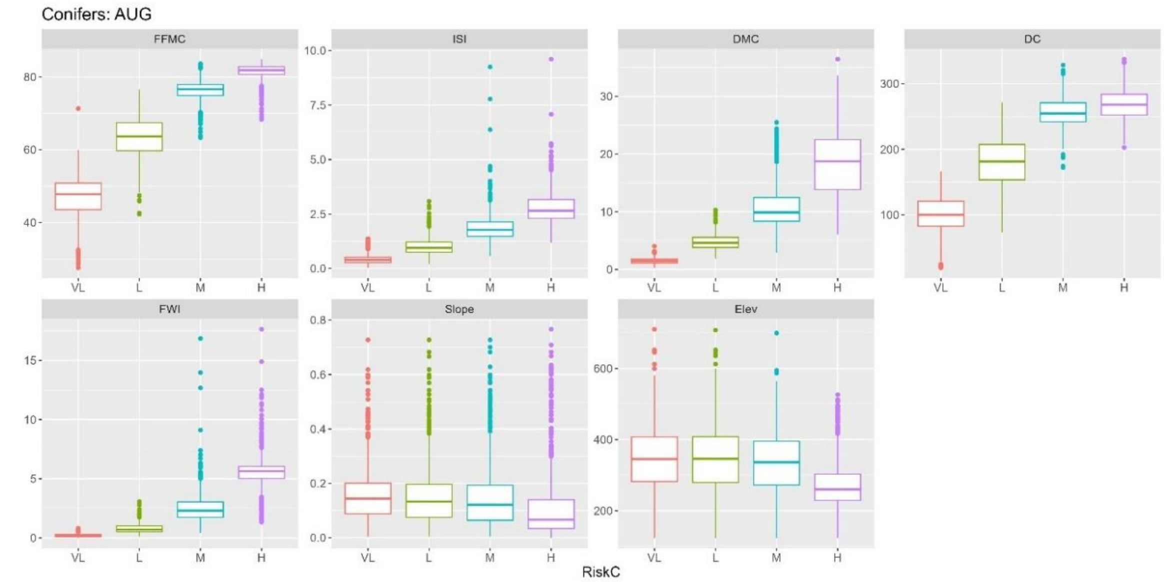
VL L M H
RiskC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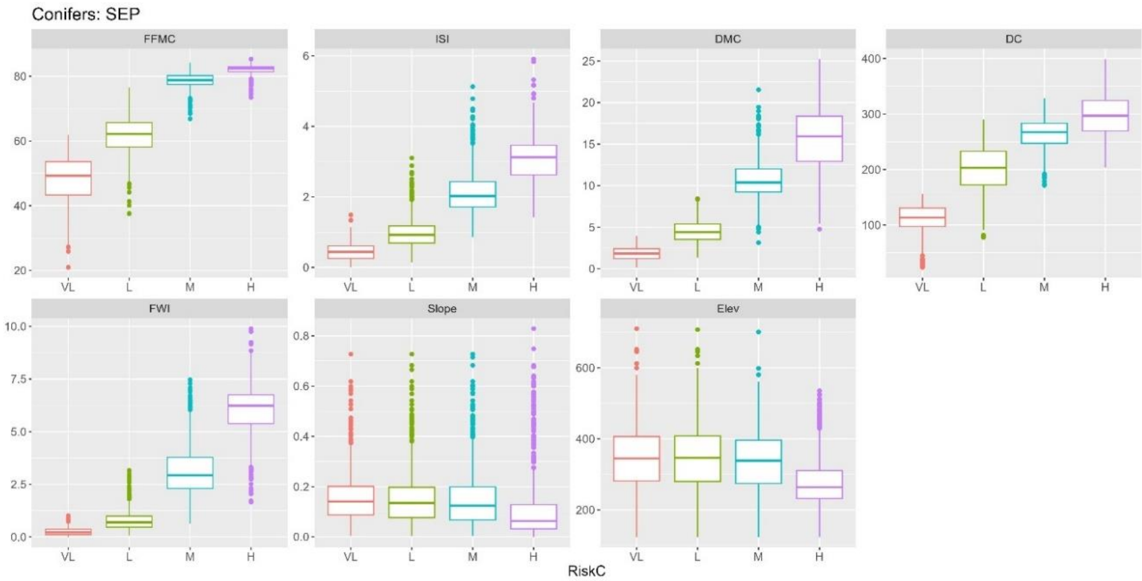
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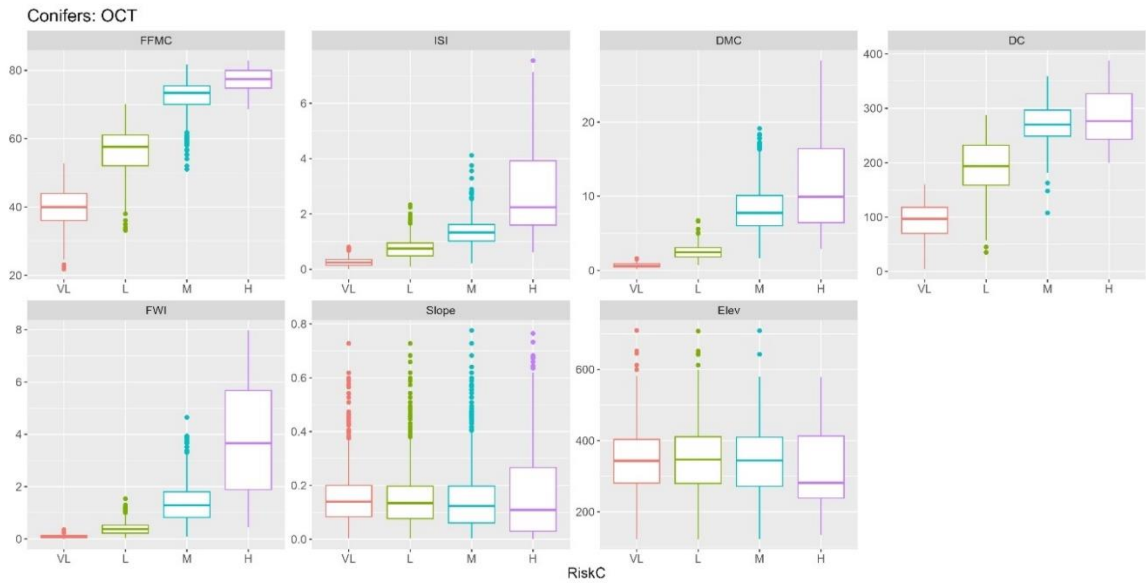
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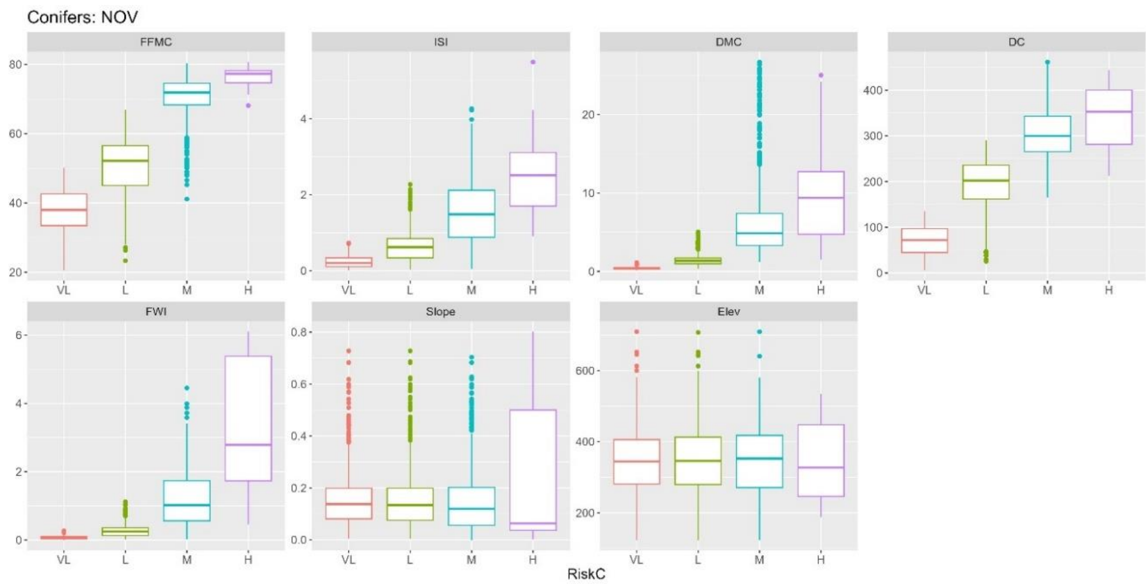
RiskC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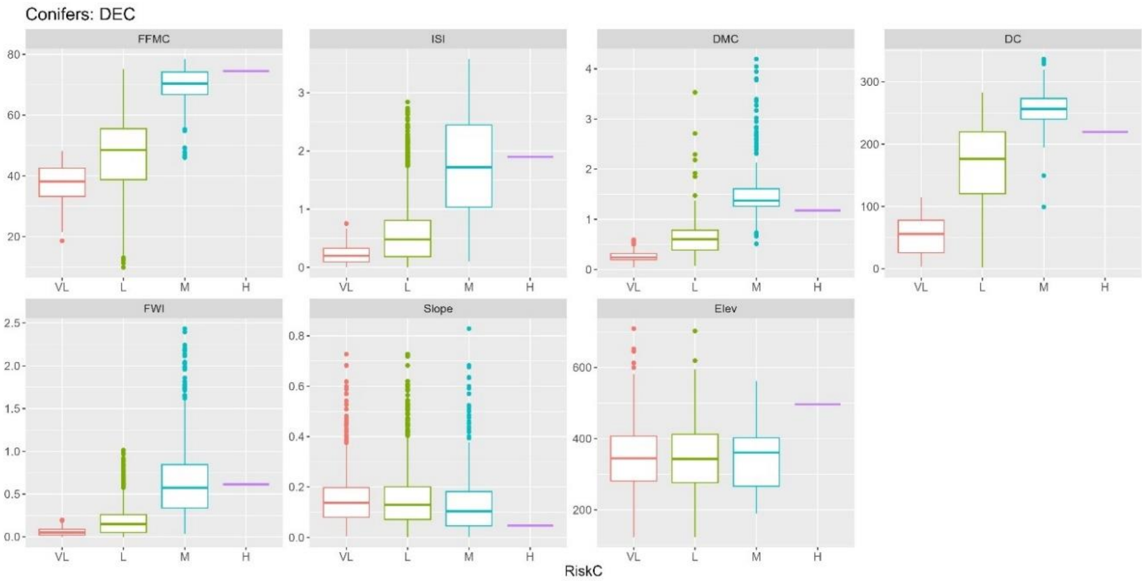
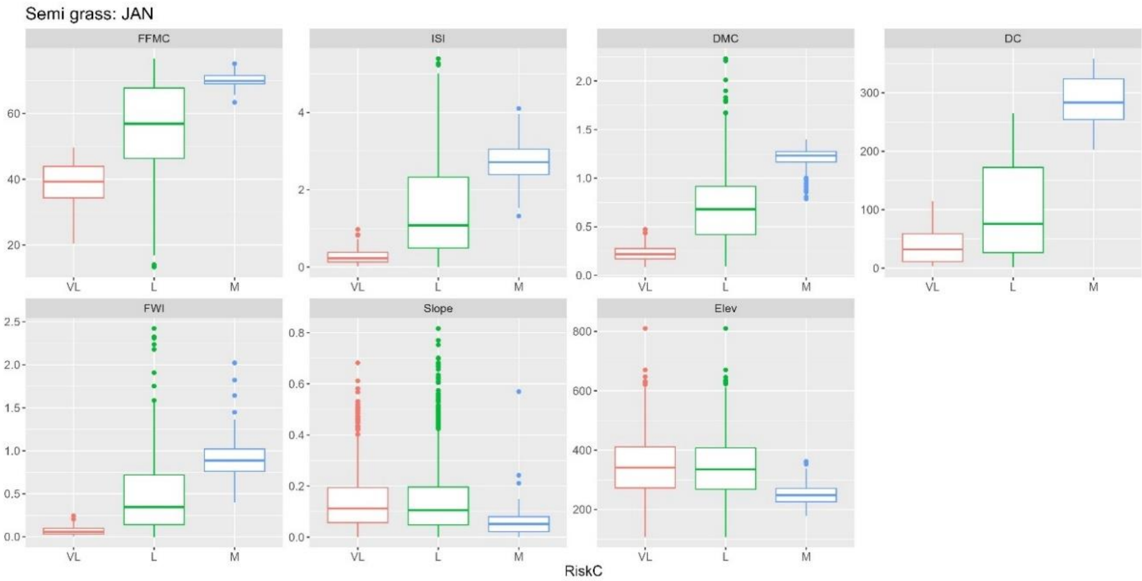
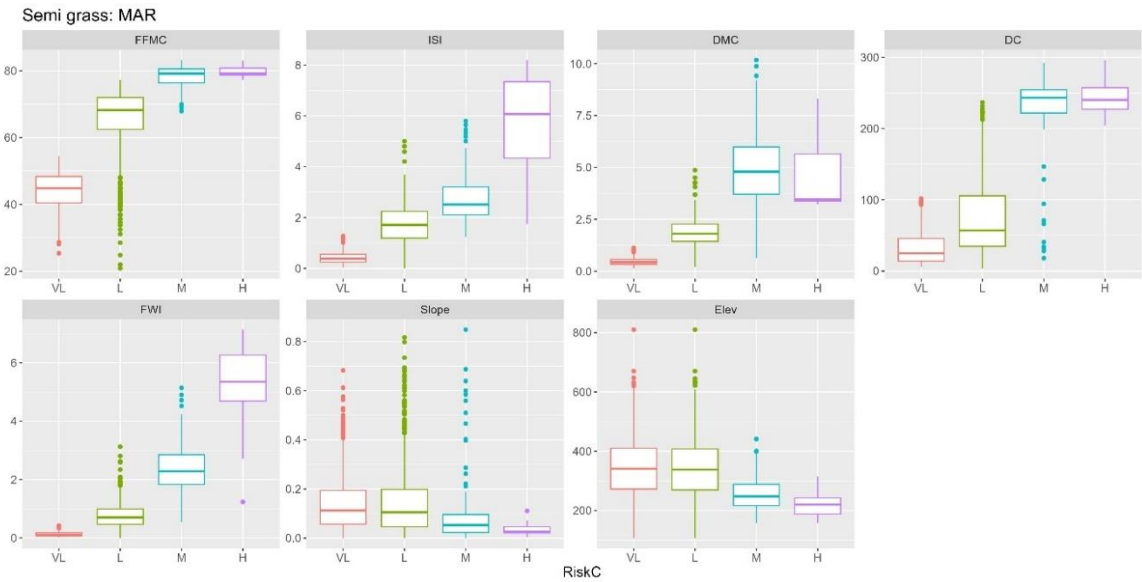
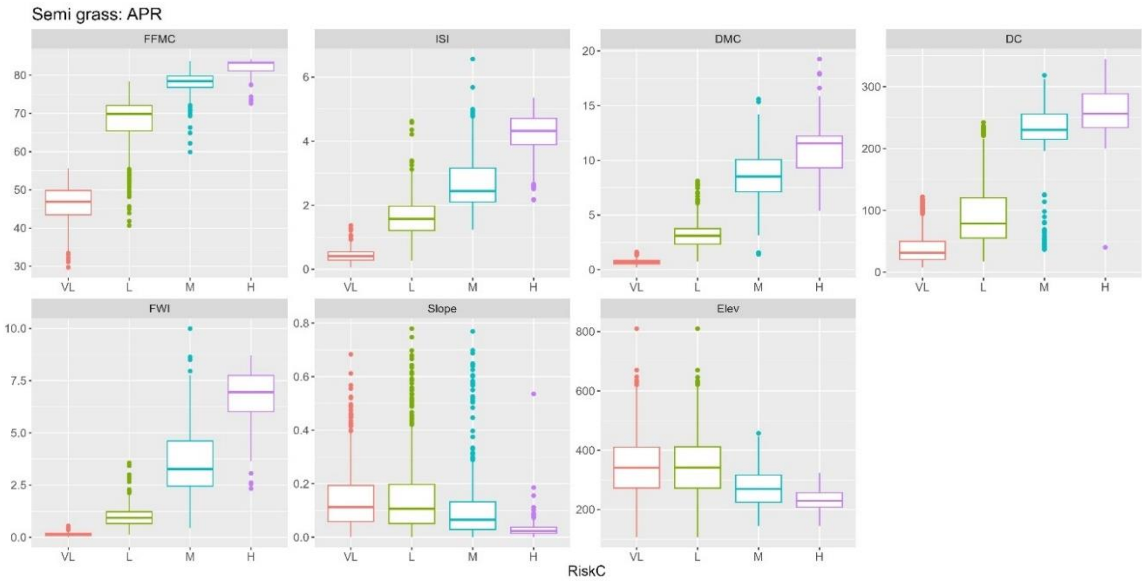
VL L M H
RiskC

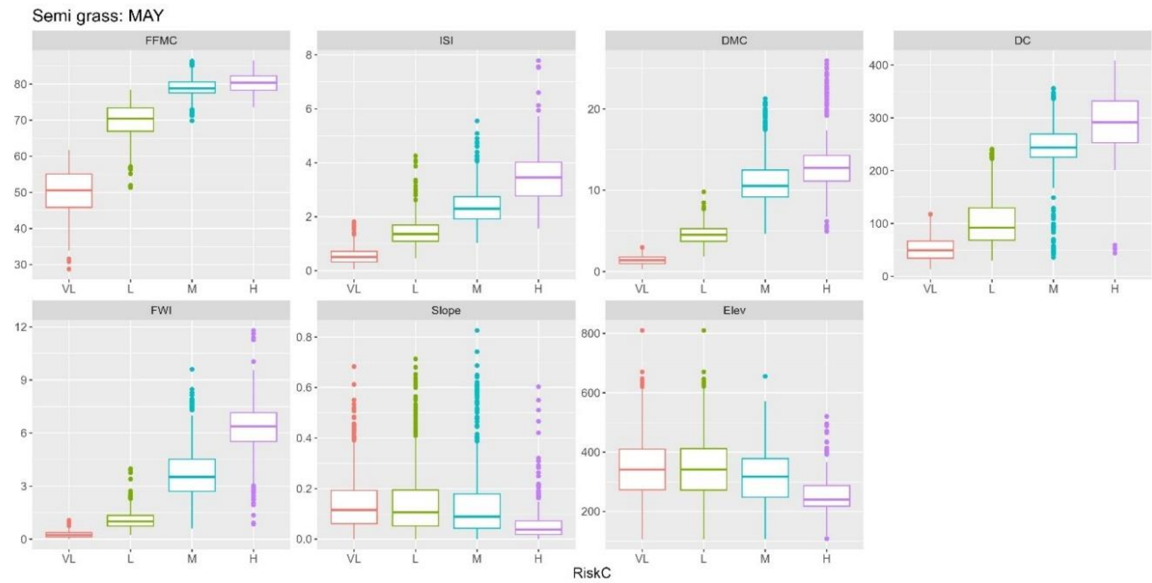


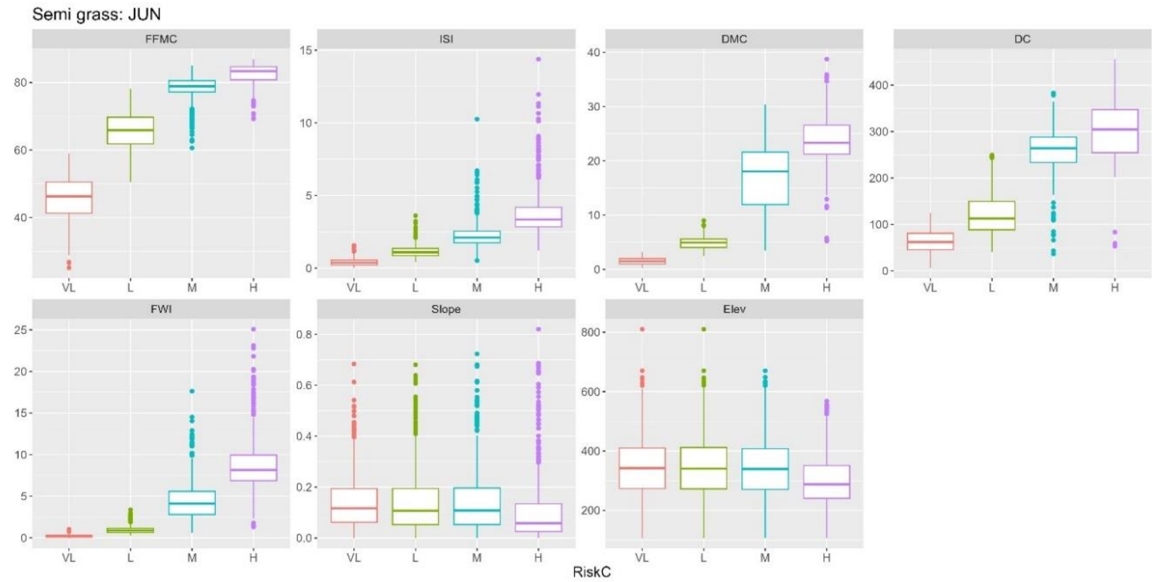
Seminatural grass

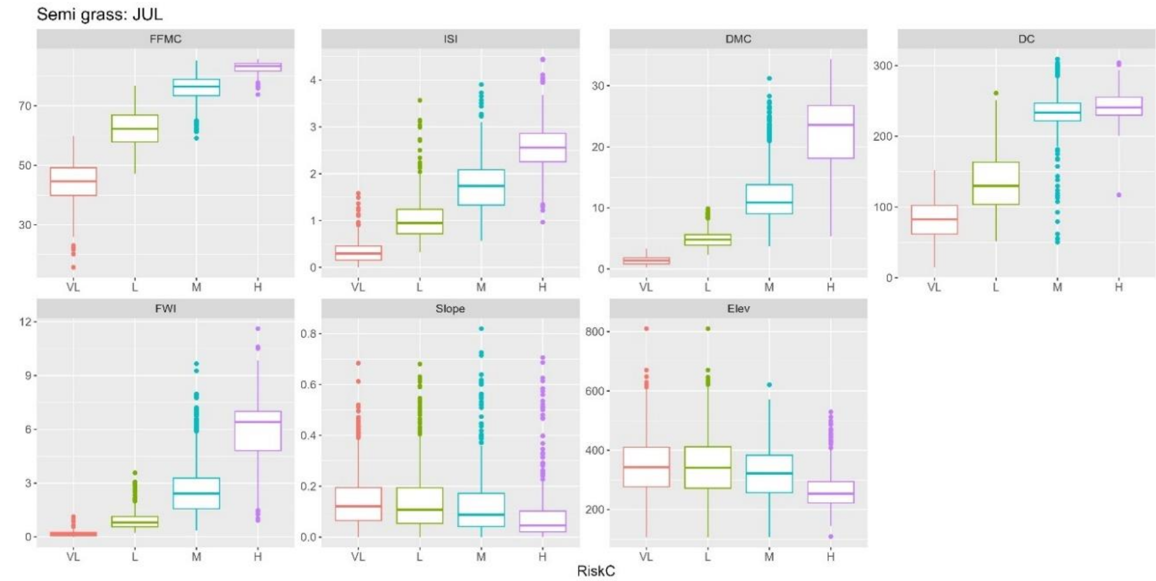


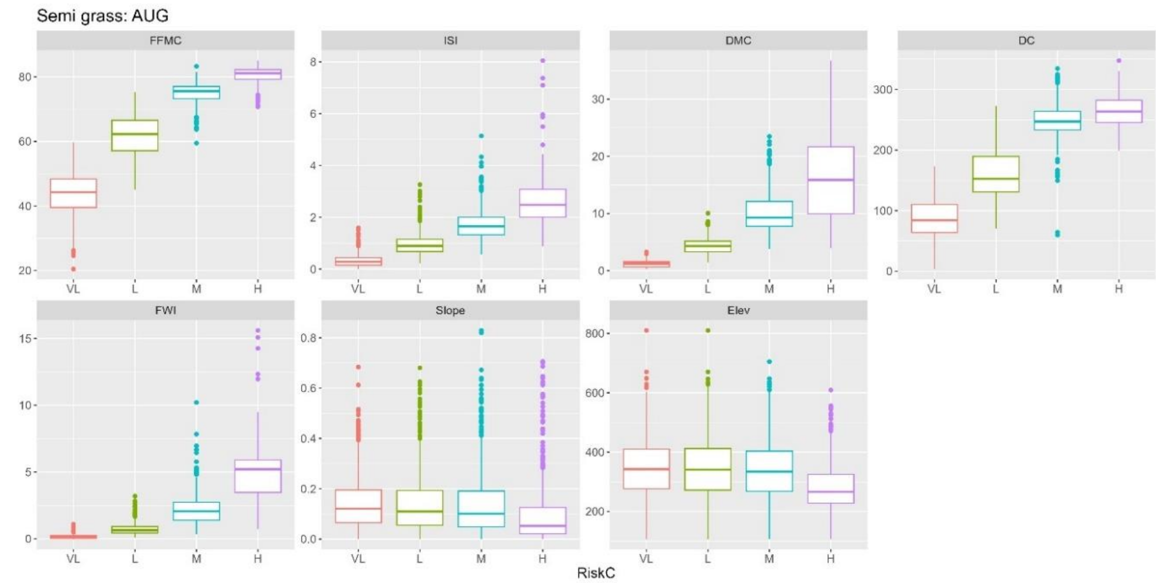


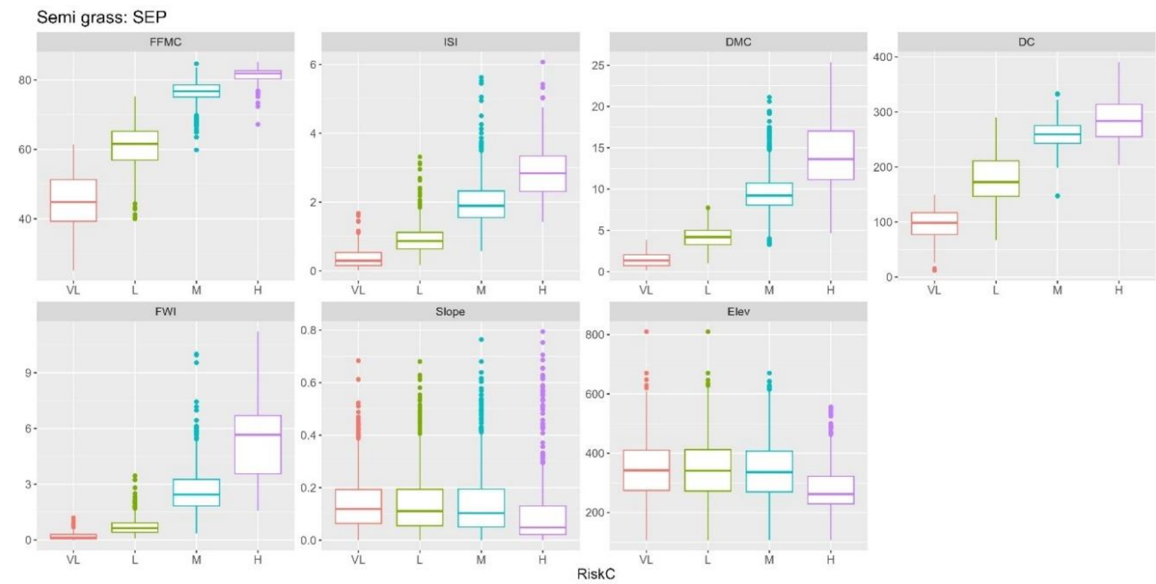

Semi grass: APR
FFMC
ISI
DMC
DC
FWI
Slope
Elev
RiskC

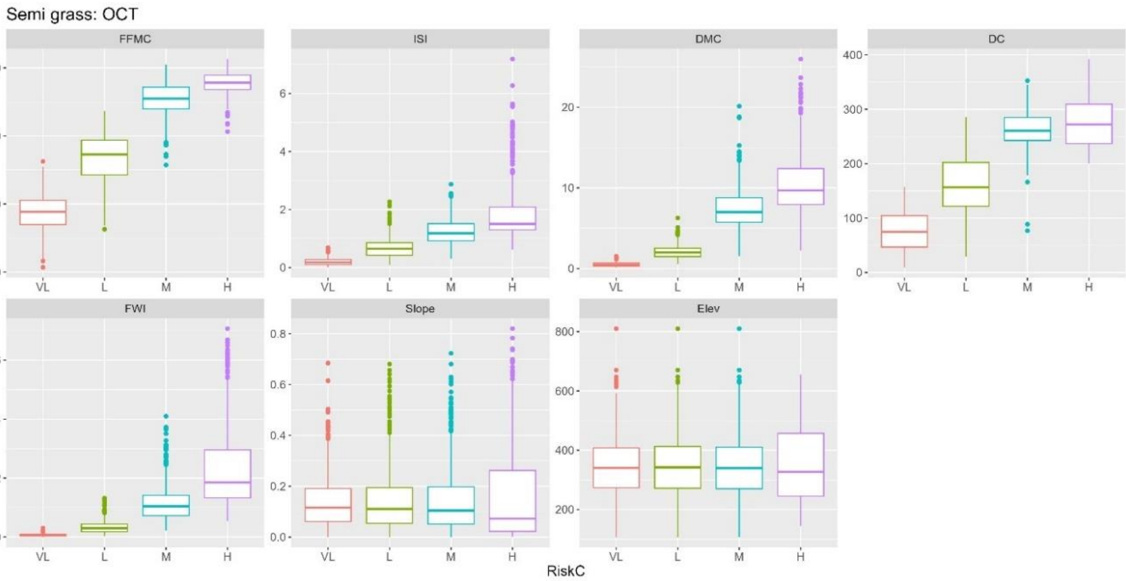

Semi grass: MAY
FFMC
ISI
DMC
DC
FWI
Slope
Elev
RiskC

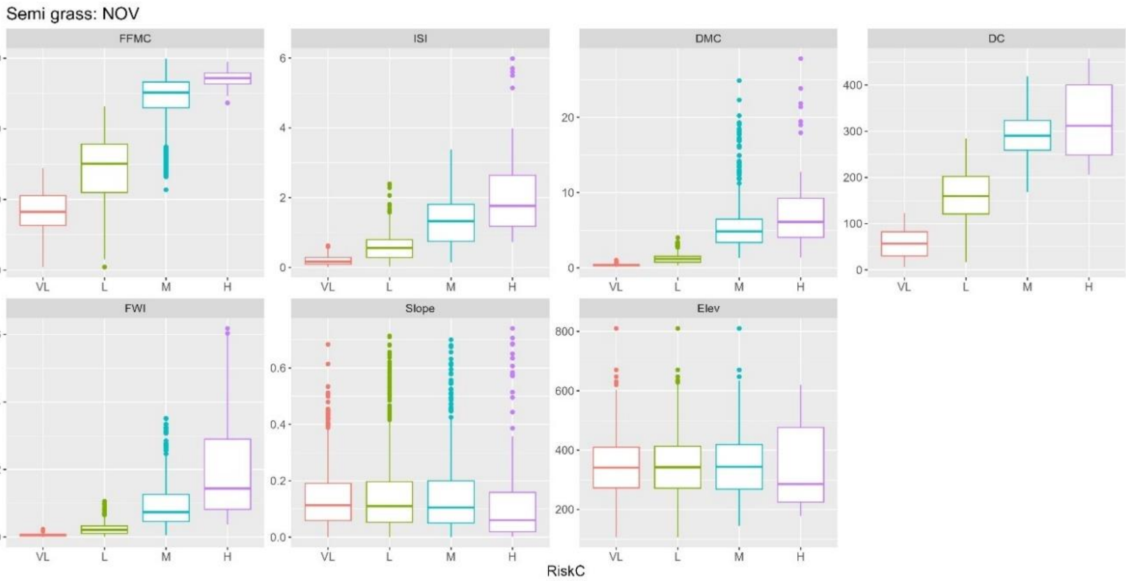

Semi grass: JUN
FFMC
ISI
DMC
DC
FWI
Slope
Elev
RiskC

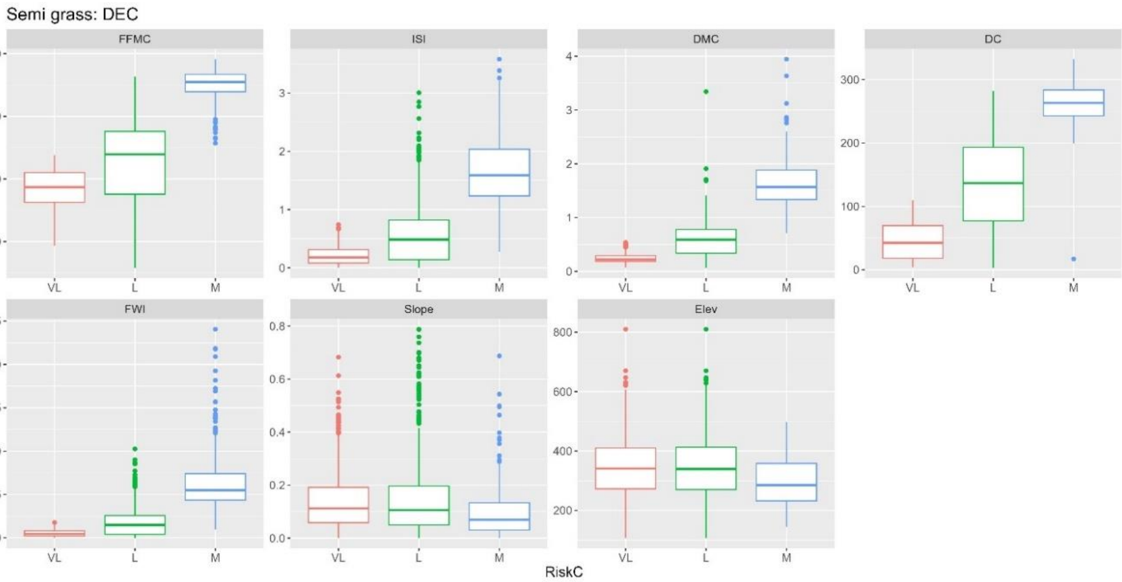

Semi grass: JUL
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC


Semi grass: AUG
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC

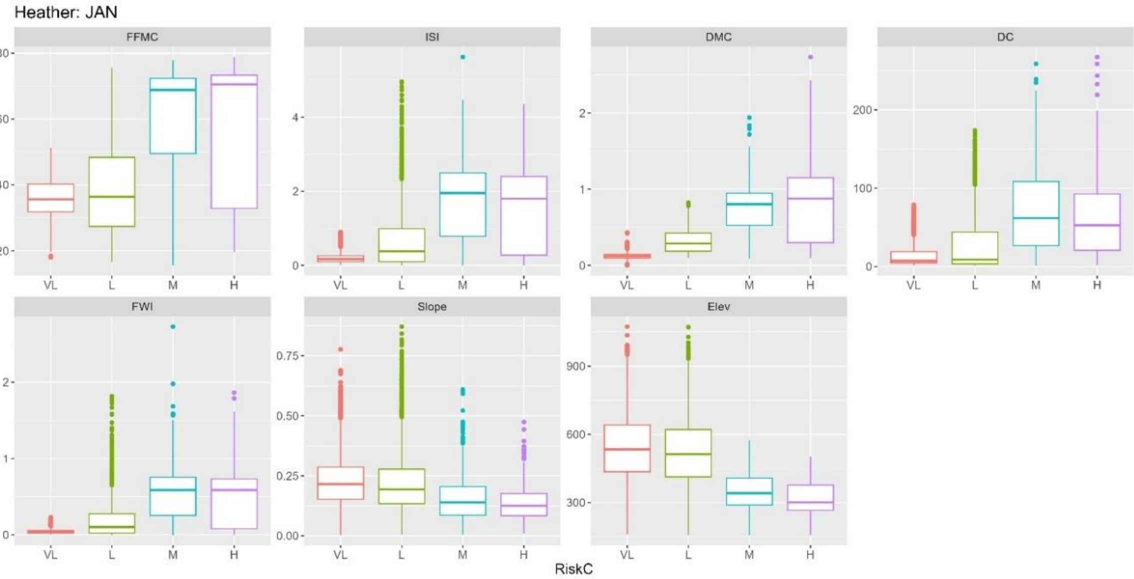

Semi grass: SEP
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC

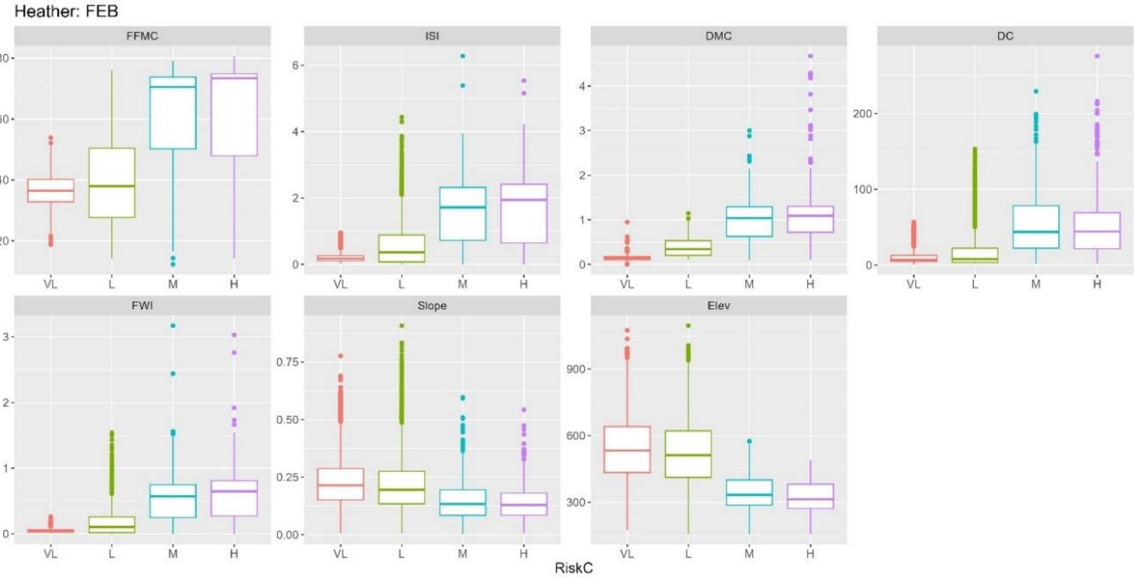

Semi grass: OCT
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC

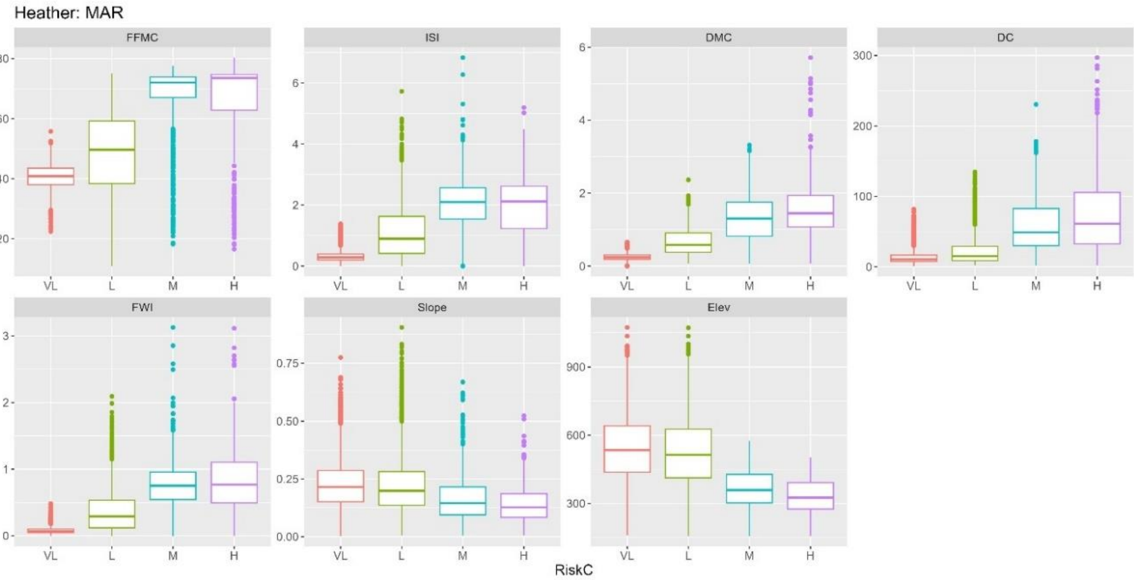

Semi grass: NOV
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC

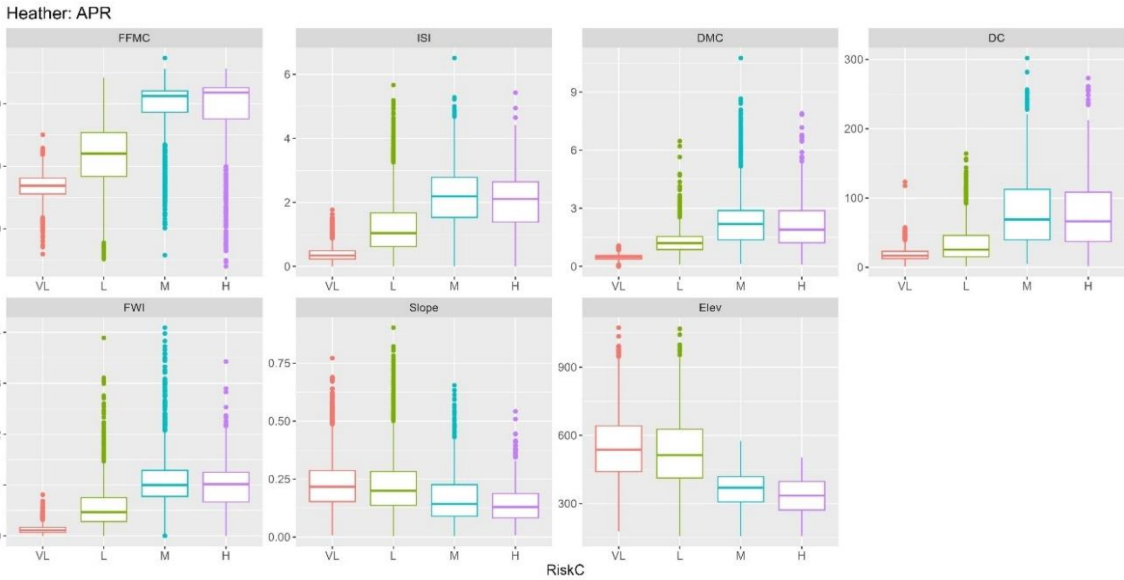

Semi grass: DEC
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M
RiskC

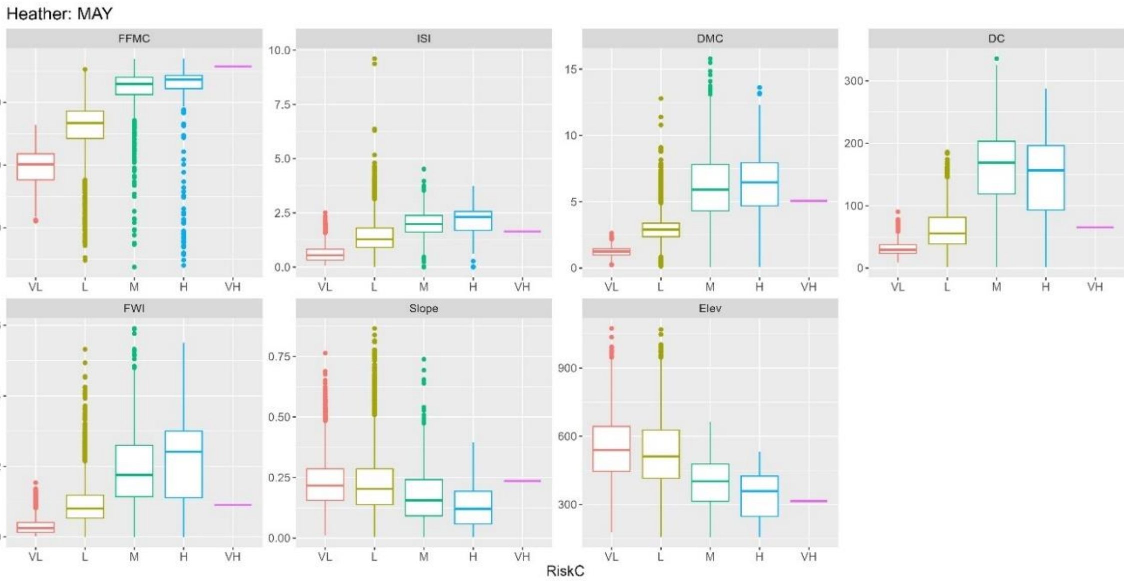
Heather

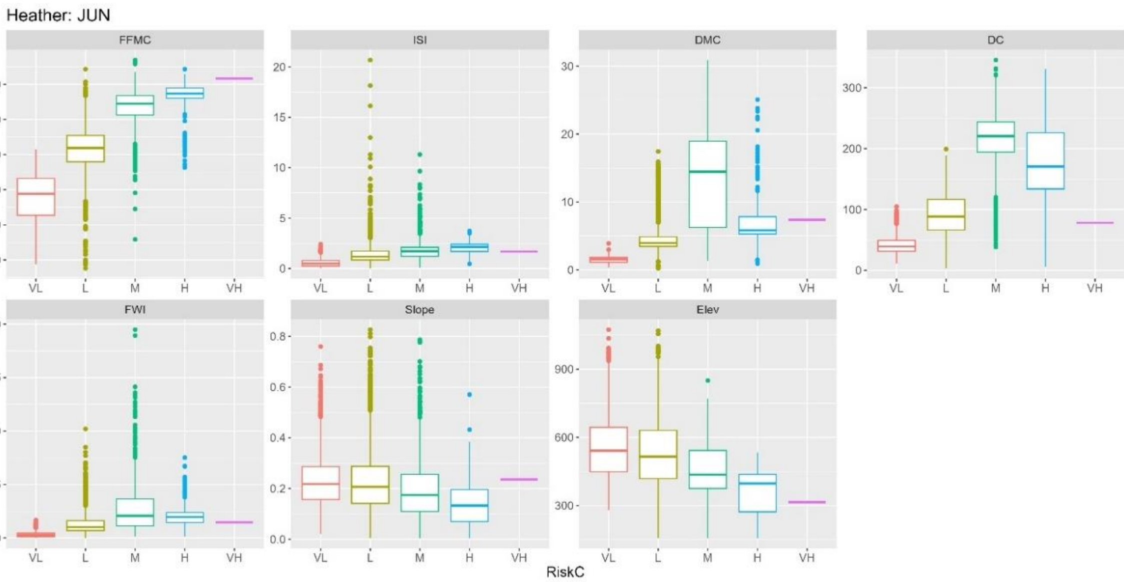

Heather: JAN
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC


Heather: FEB
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC


Heather: MAR
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC


Heather: APR
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC


Heather: MAY
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M H VH
RiskC


Heather: JUN
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ISI
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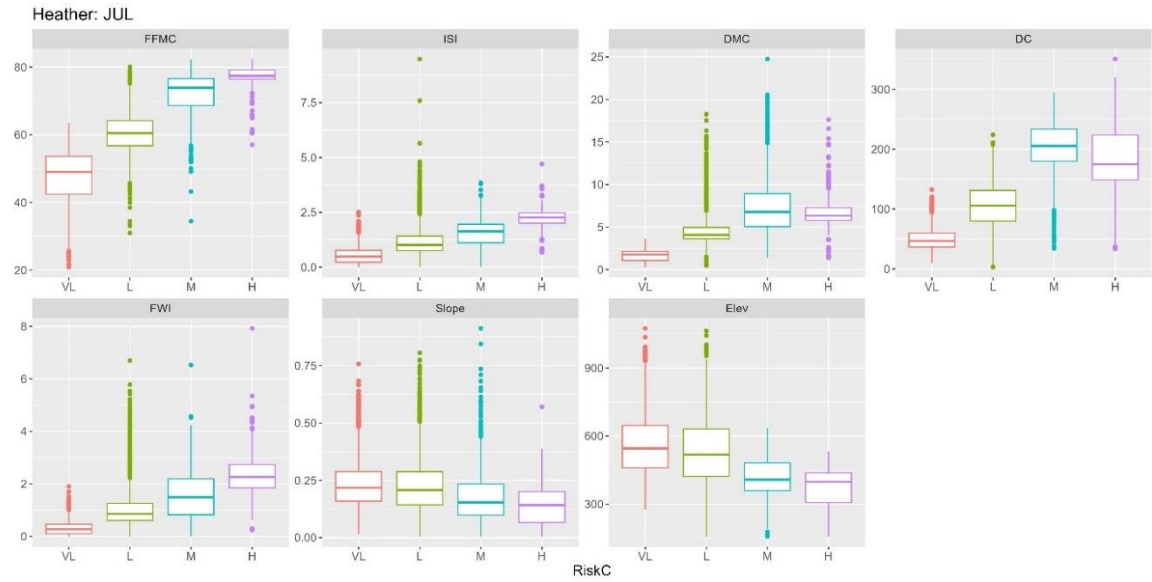
DC
FWI
Slope
Elev
VL L M H VH
RiskC


Heather: JUL
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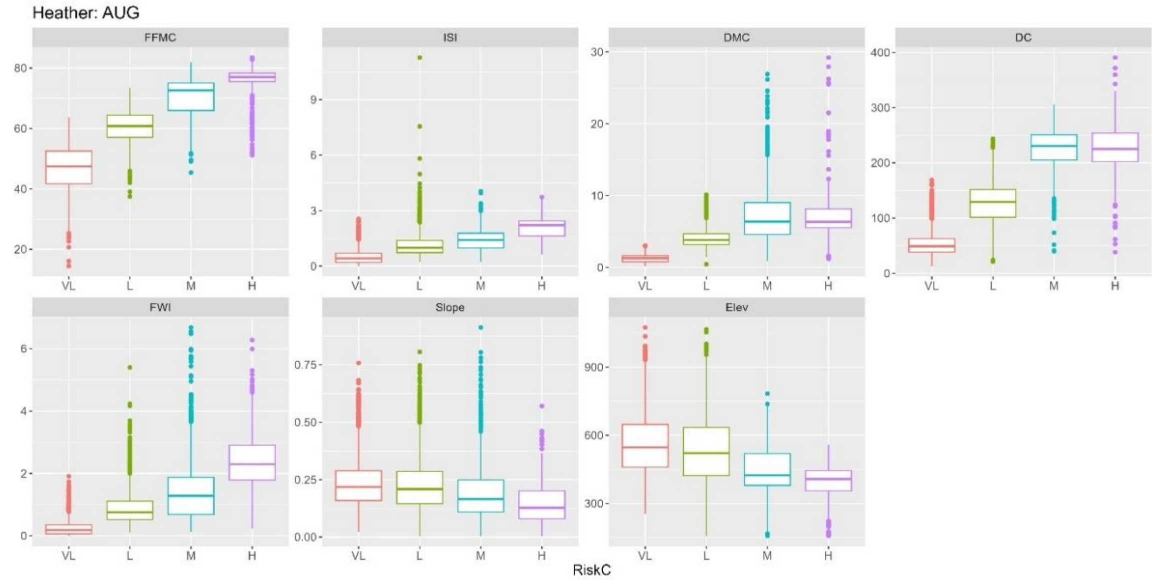
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC


Heather: AUG
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ISI
DMC
DC
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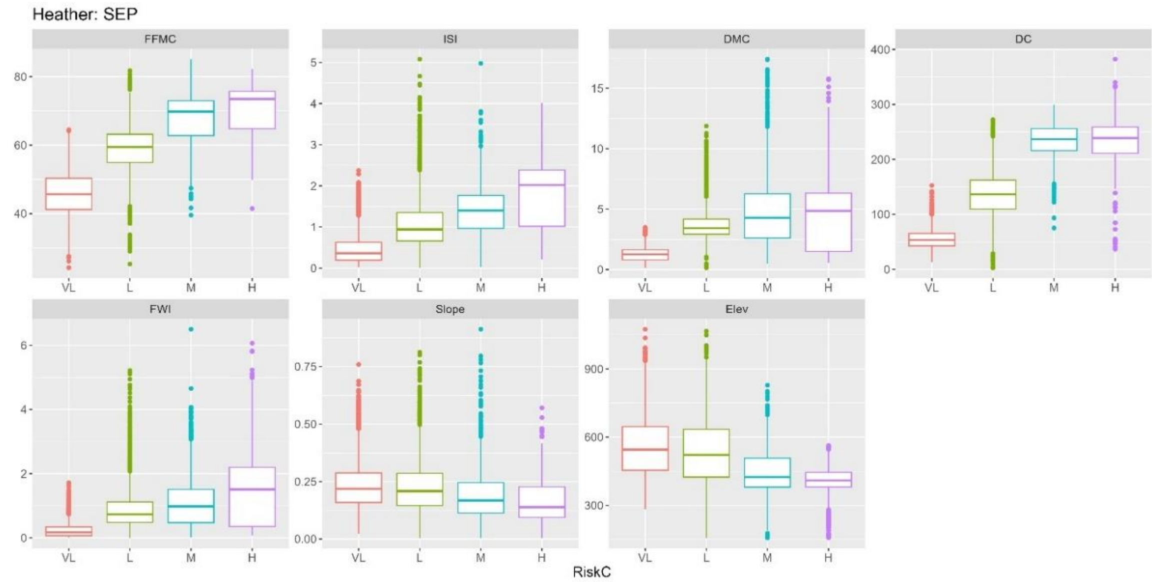
Slope
Elev
VL L M H
RiskC


Heather: SEP
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ISI
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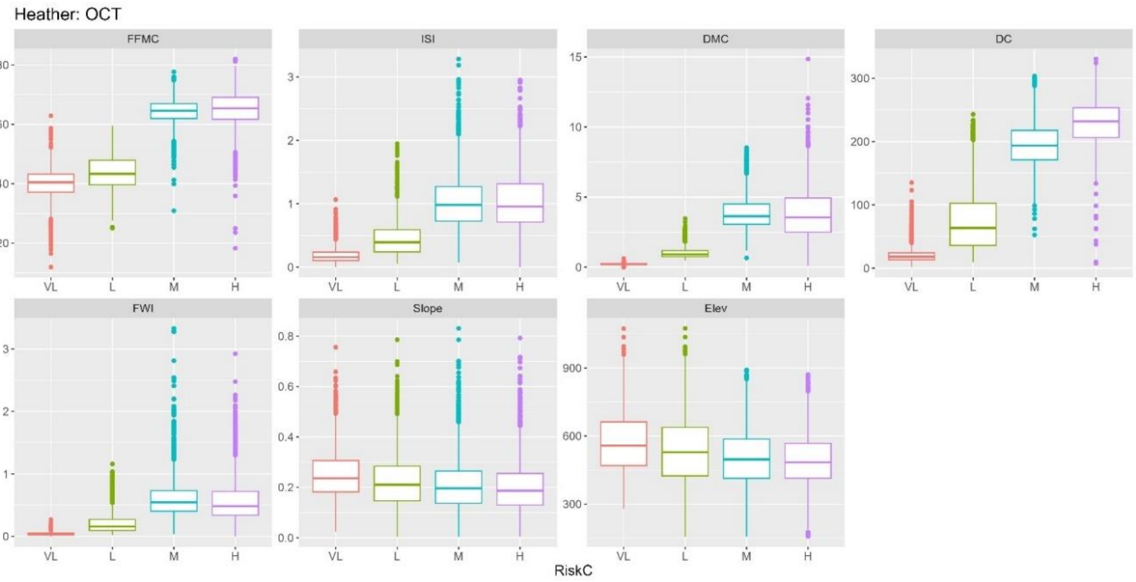
Elev
VL L M H
RiskC


Heather: OCT
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ISI
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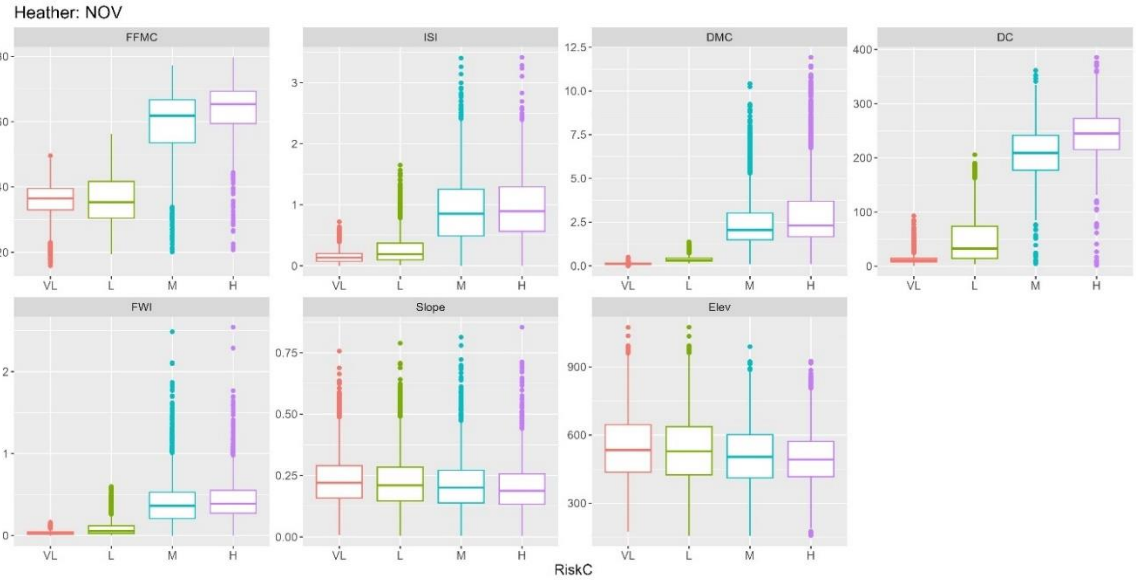
DC
FWI
Slope
Elev
VL L M H
RiskC


Heather: NOV
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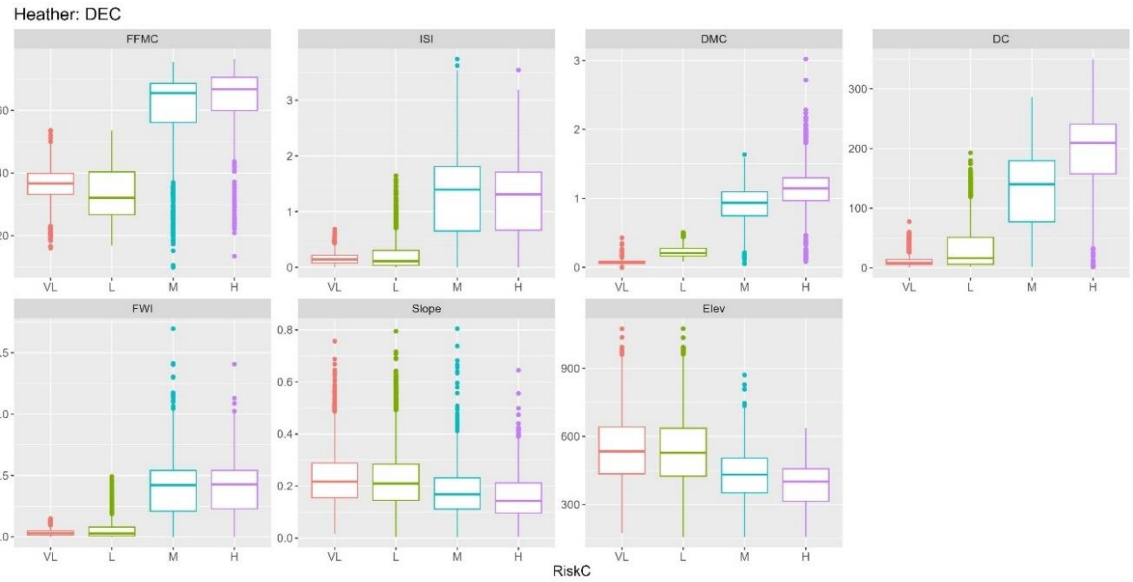
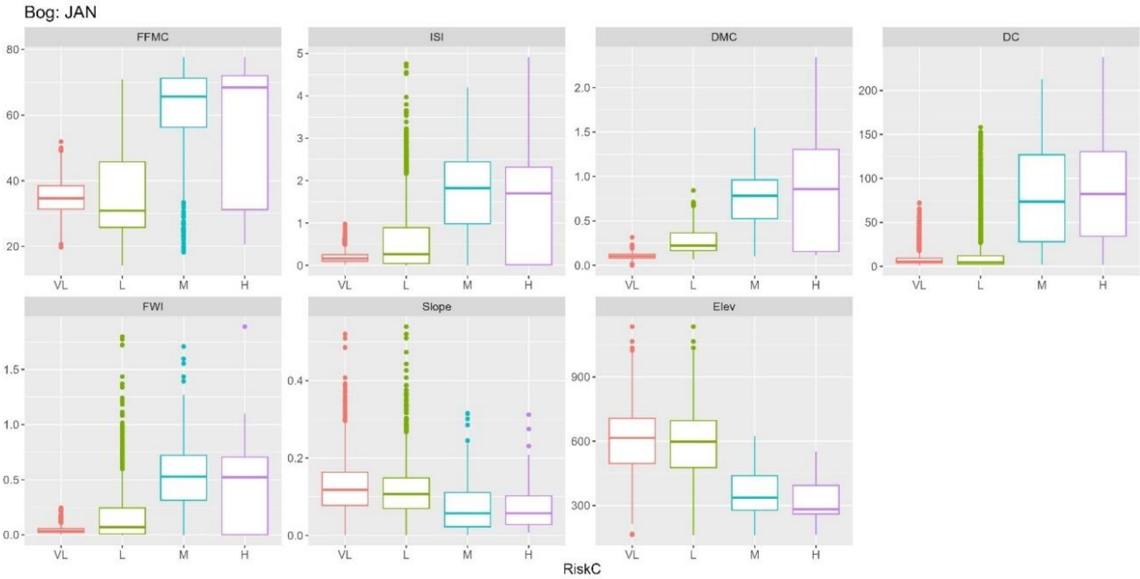
DC
FWI
Slope
Elev
VL L M H
RiskC


Heather: DEC
FFMC
ISI
DMC
DC
FWI
Slope
Elev
VL L M H
RiskC

Bog


Bog: JAN
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Slope
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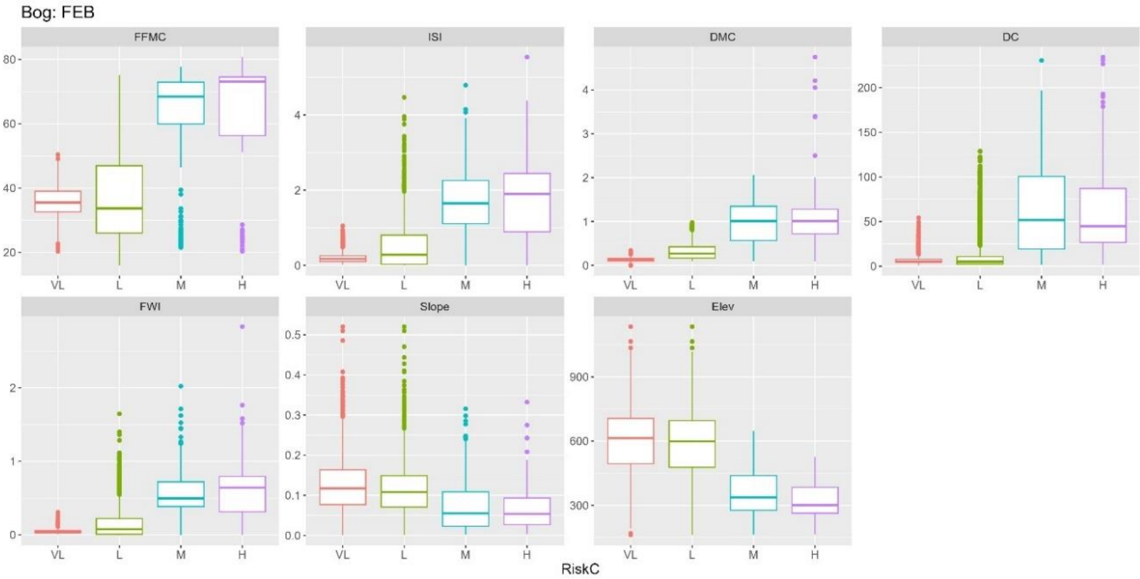
M
H
RiskC


Bog: FEB
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Slope
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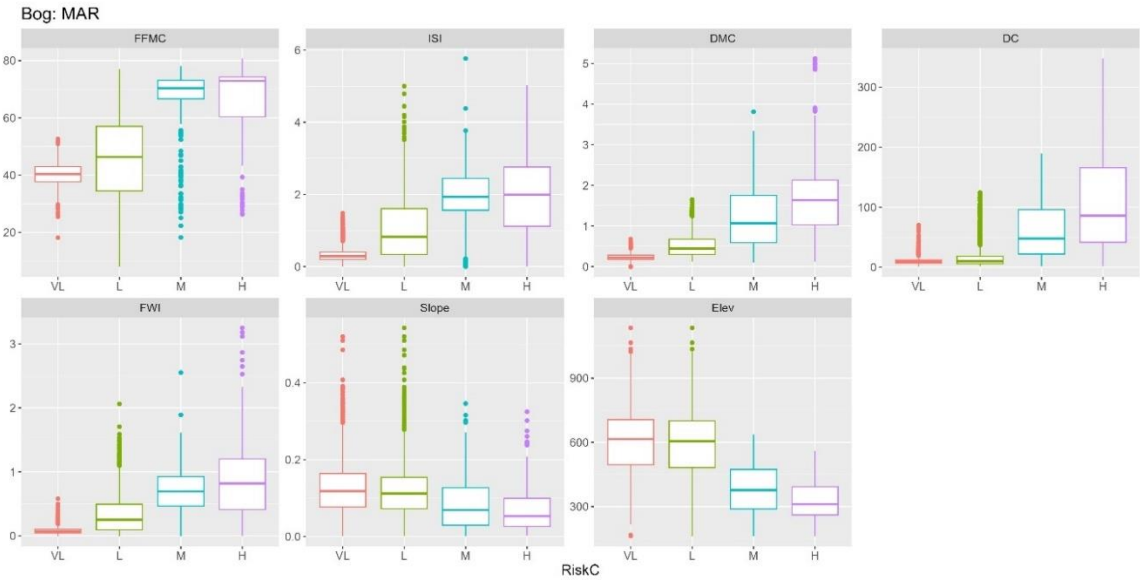
H
RiskC


Bog: MAR
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DC
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Slope
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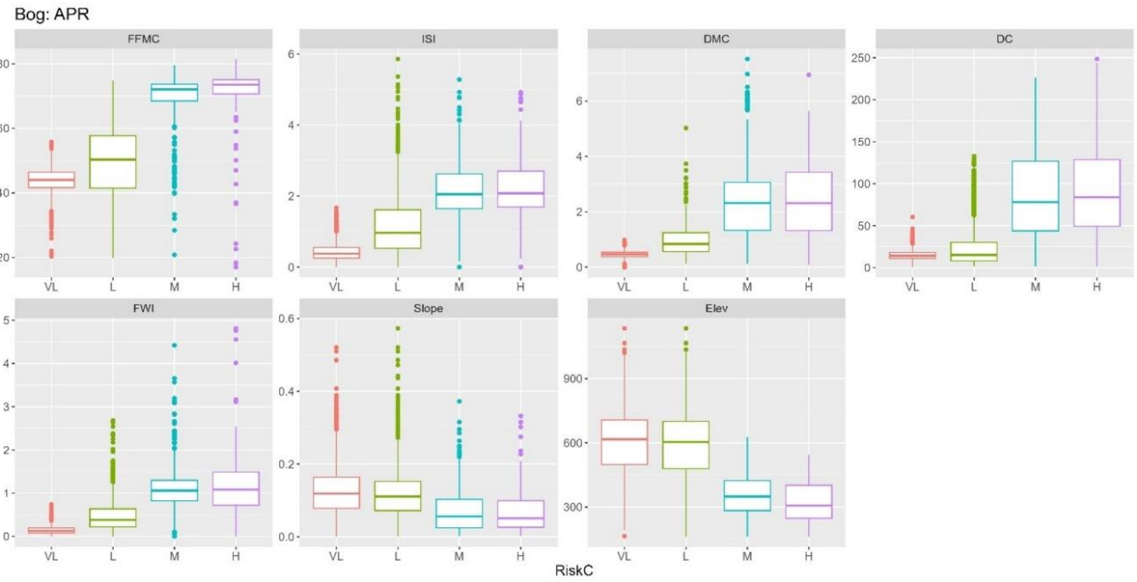
L
M
H
RiskC


Bog: APR
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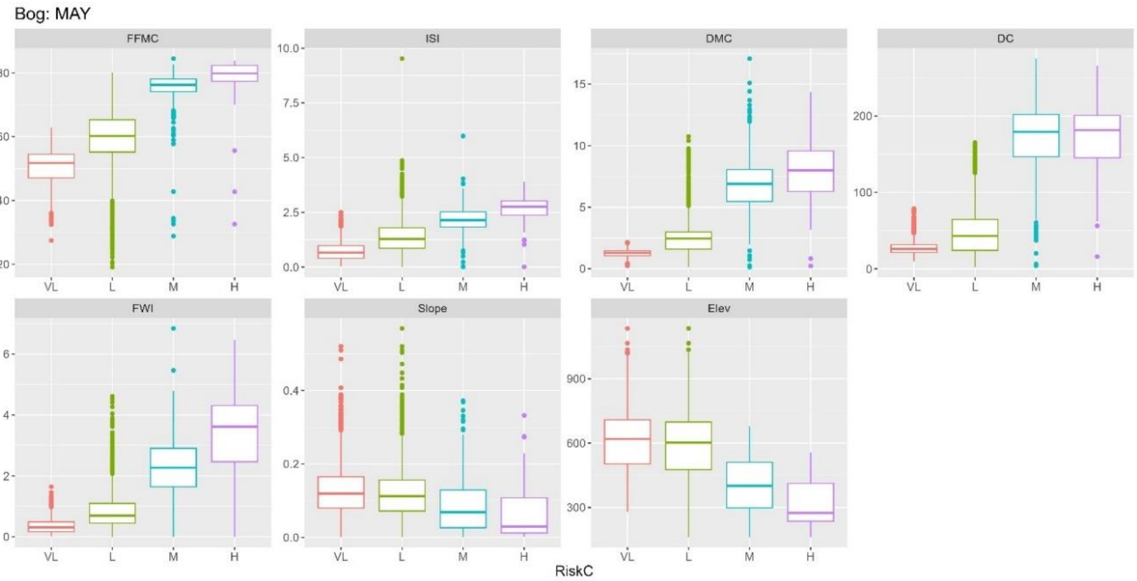
RiskC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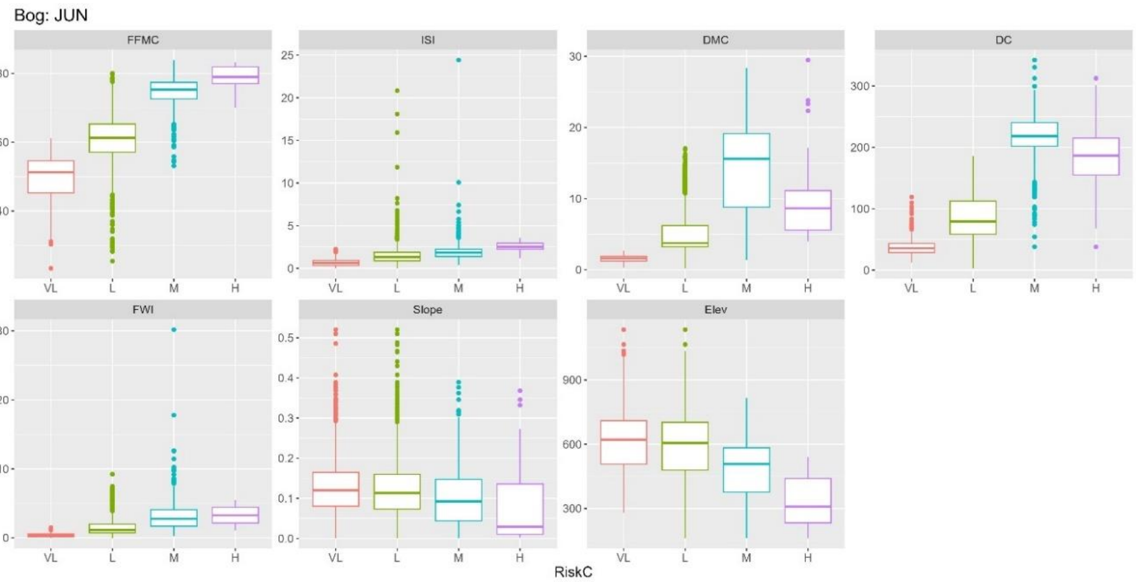
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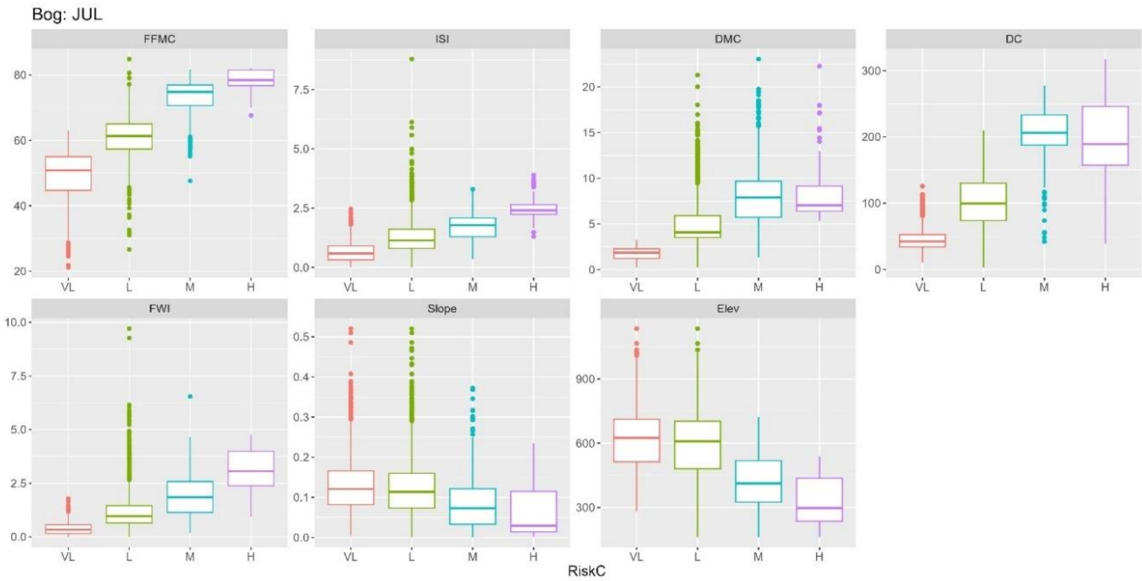
RiskC


Bog: JUL
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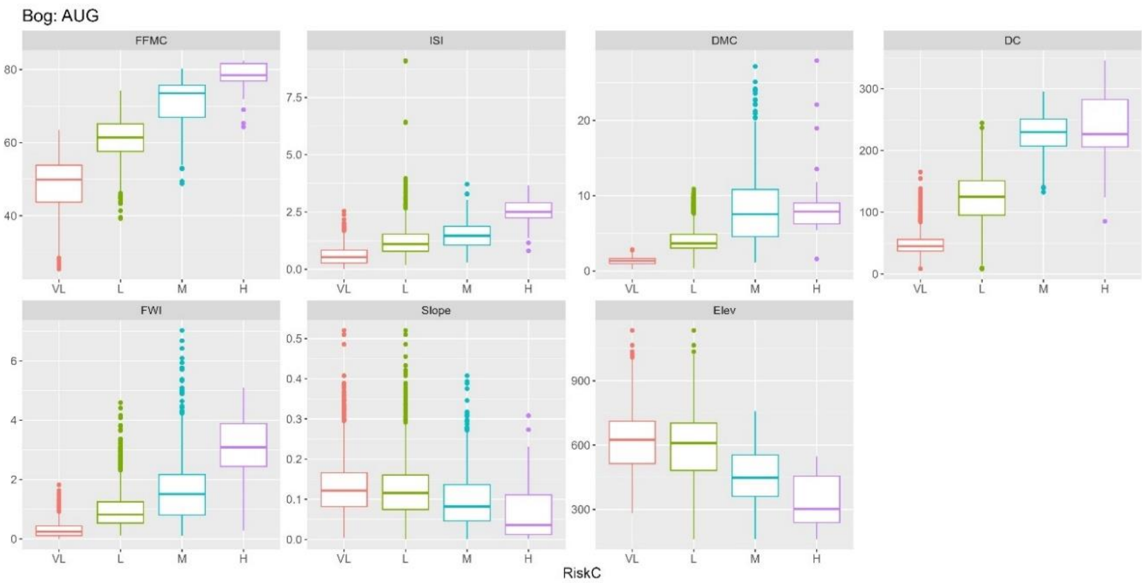
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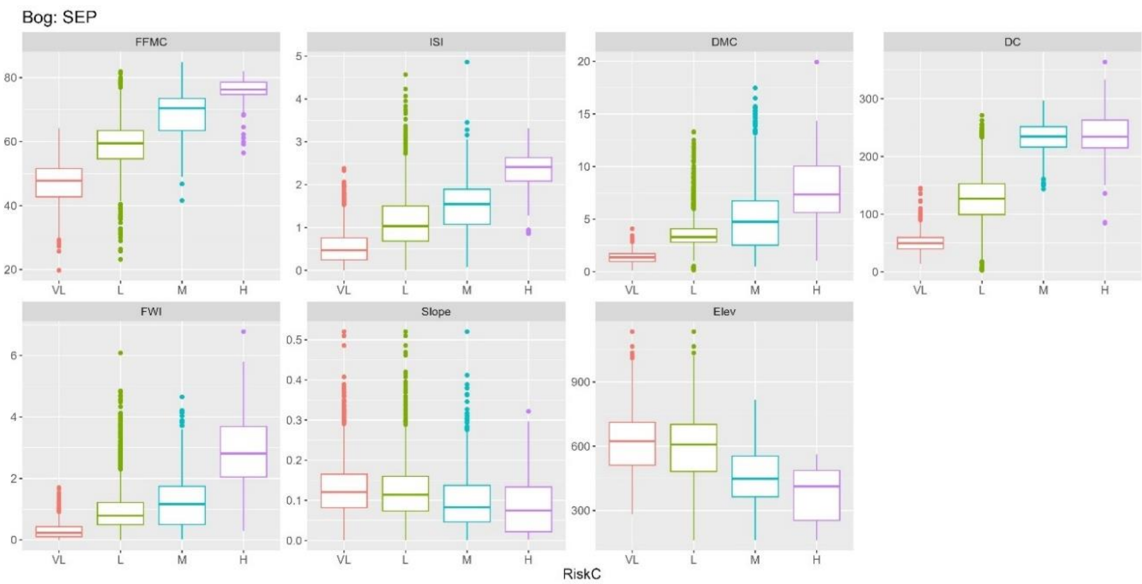
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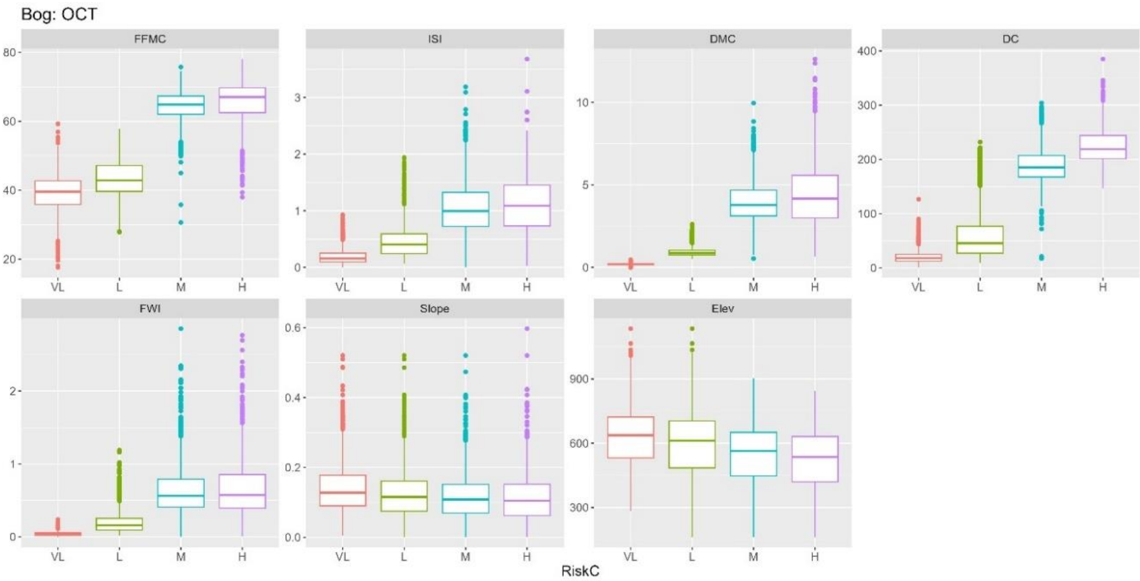
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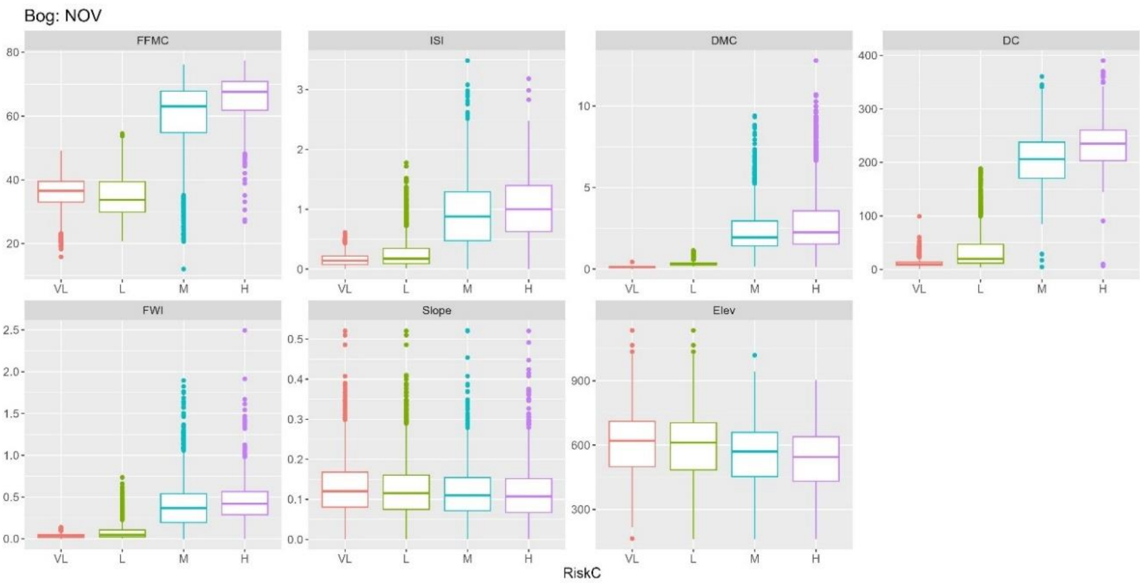
M
H
RiskC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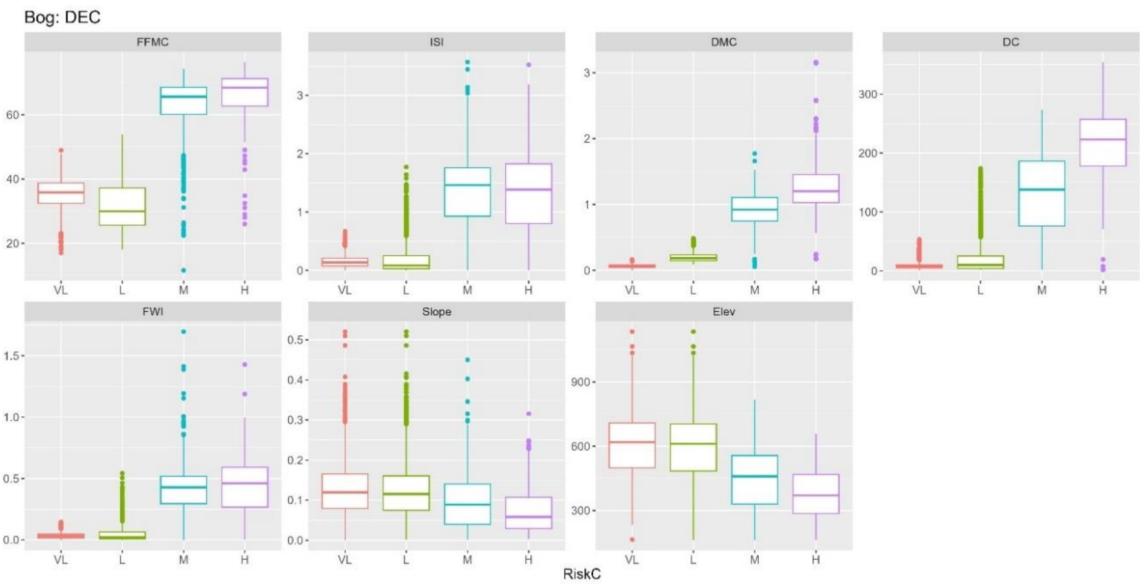
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Elev
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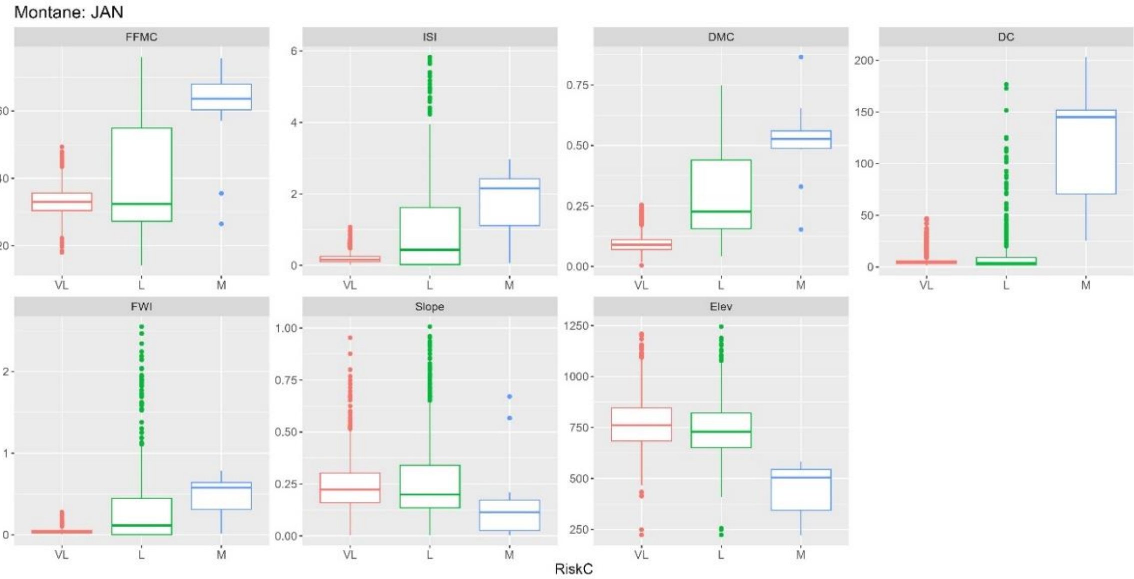
RiskC

Montane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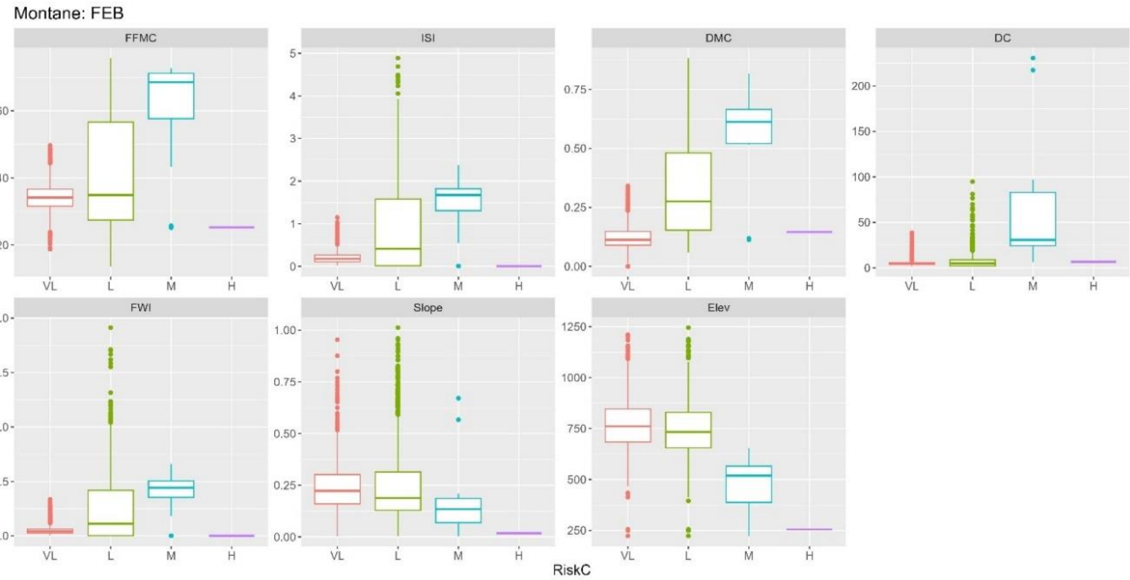
RiskC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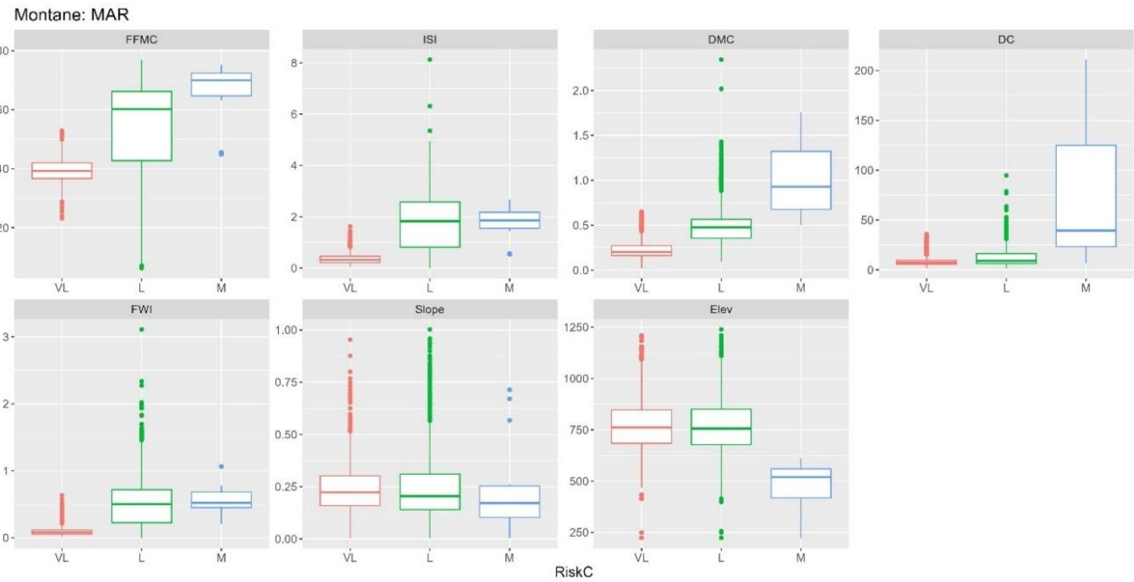
RiskC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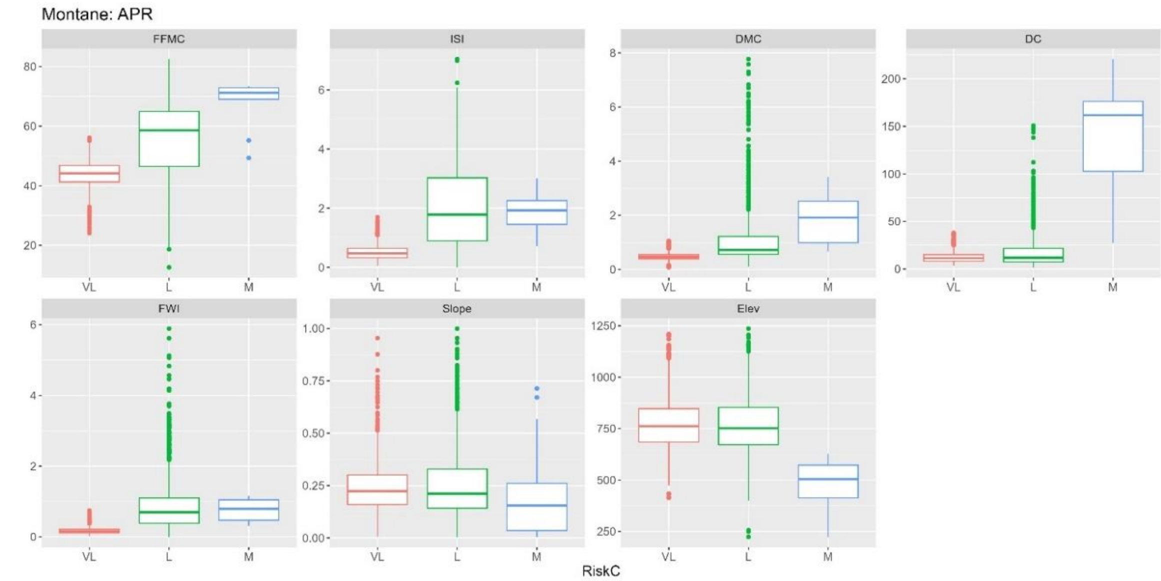
RiskC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DMC
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M
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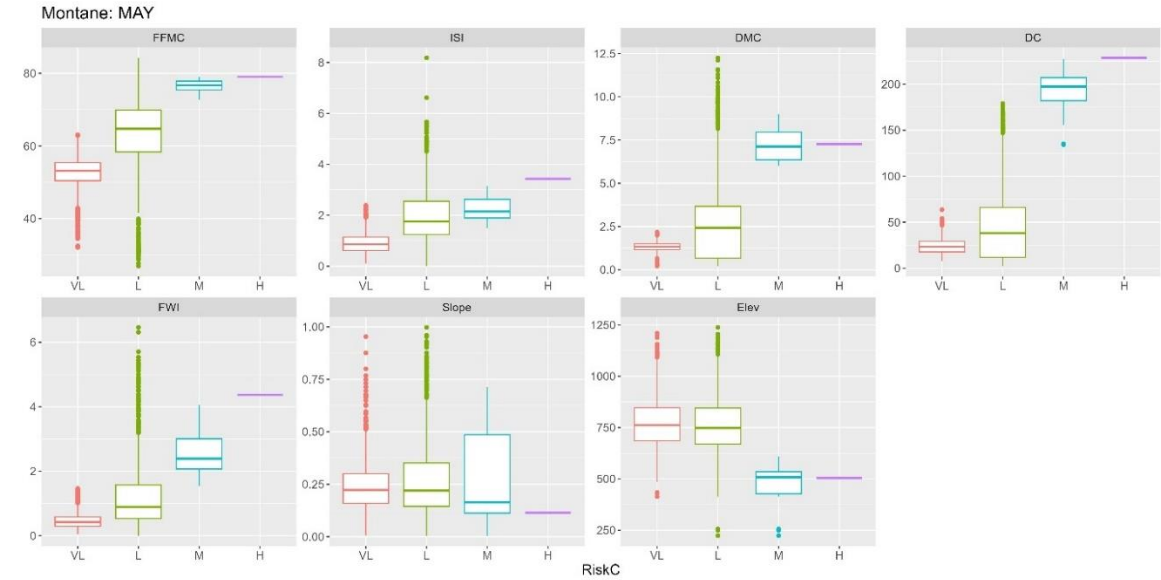
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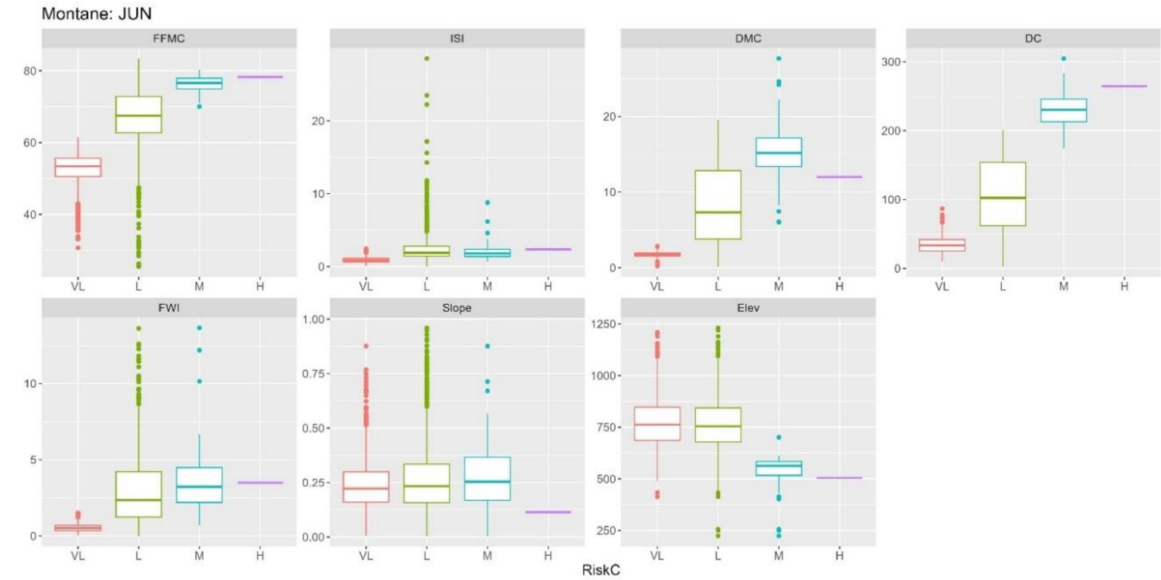
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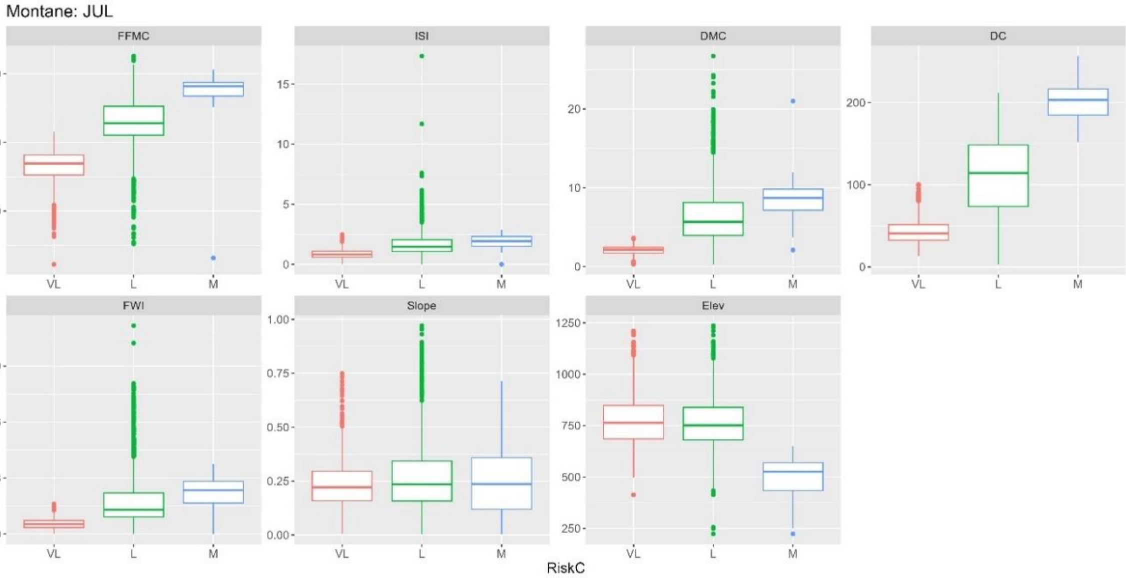
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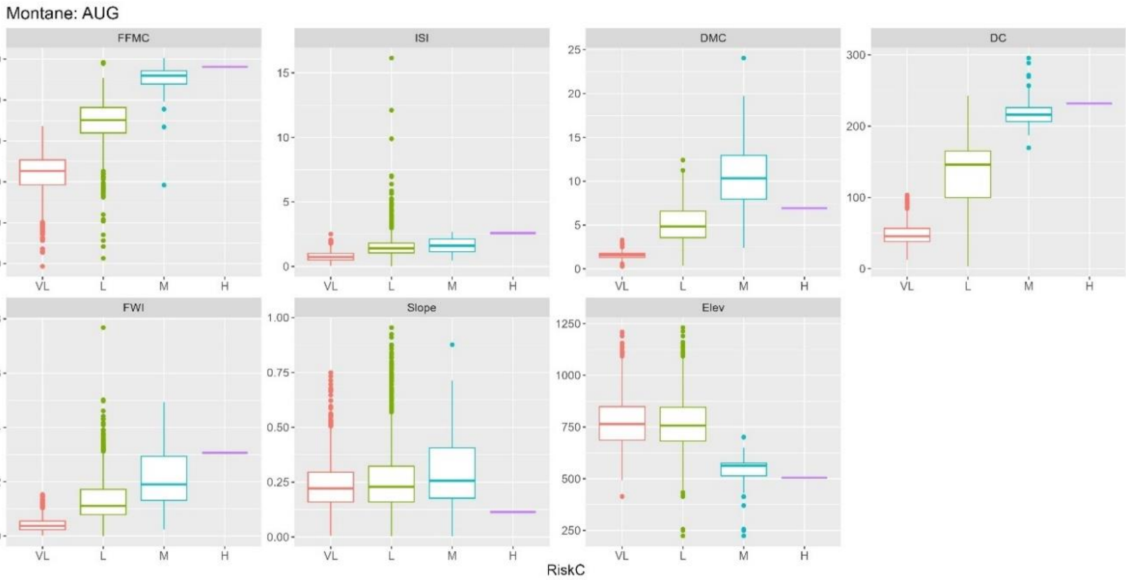
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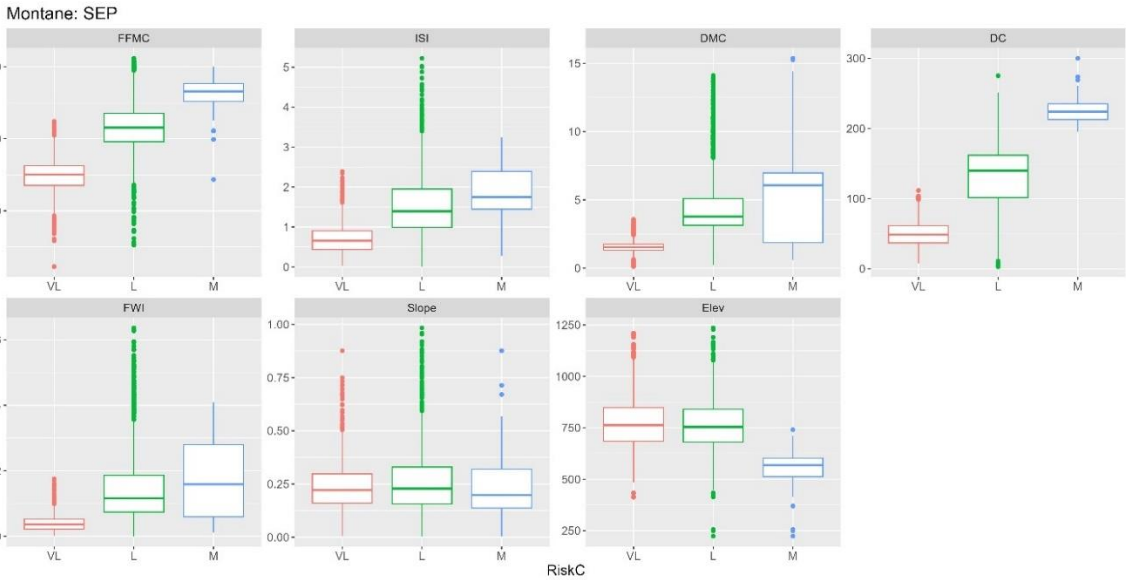
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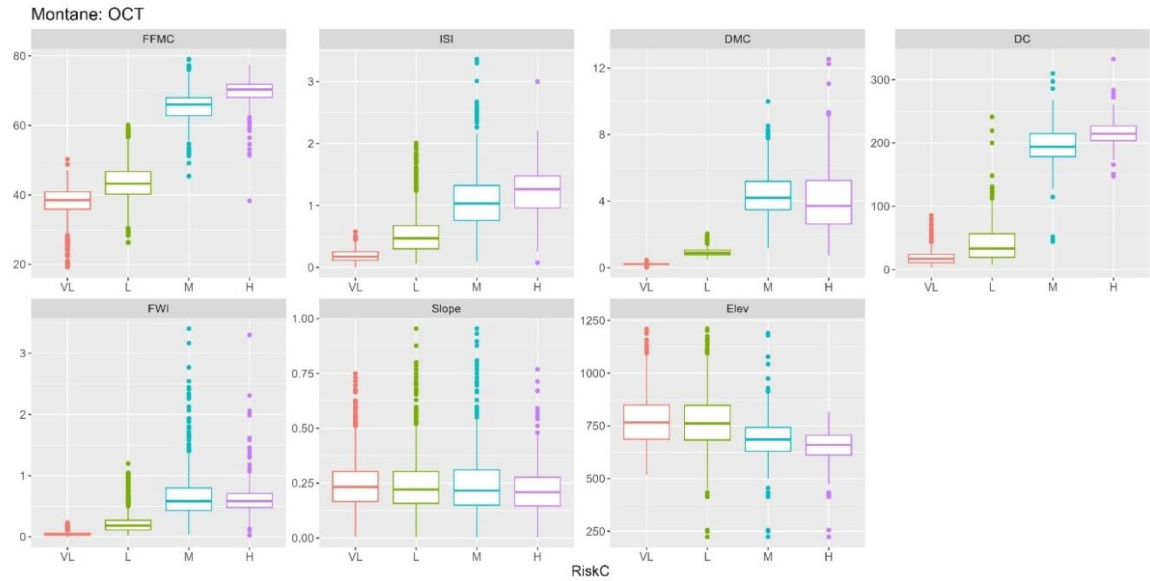
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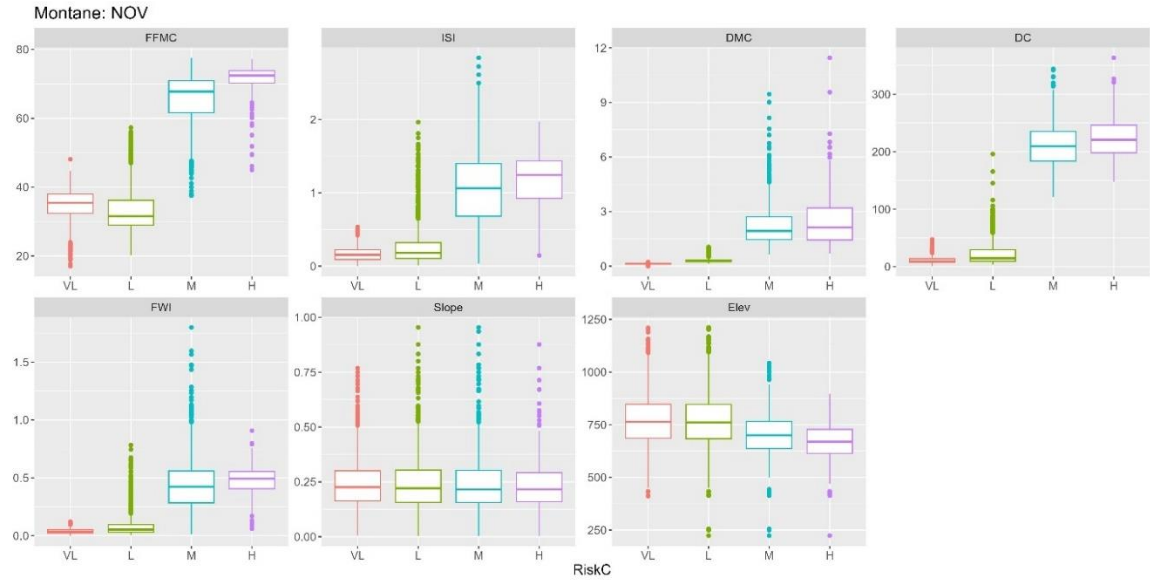
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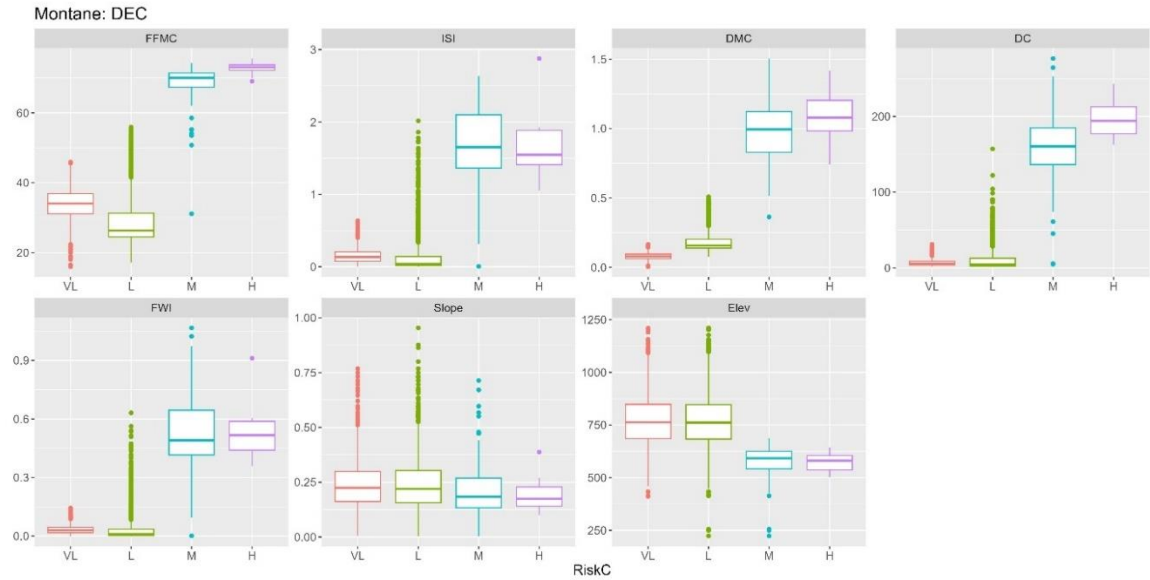
Montane: DEC
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DC
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Slope
Elev
RiskC

The James Hutton Institute