Predicting Live Fuel Moisture Content in Southern California

Antoine Carnec Clinton Leung

1. INTRODUCTION

As the world has increasingly witnessed the rise of wildfires due to climate change, it is an important topic to improve predictive models for the ignition, spread, and severity of wildfires. Research has shown that the fuel moisture content of vegetation is an important determining factor in the ignition, behaviour and severity of wildfires (Ruffault et al., 2018). The fuel moisture content of vegetation can be split up into two categories: live fuel moisture content (LFMC) and dead fuel moisture content (DFMC). Both have been found to have crucial effects on the spread of wildfires. There are many models that predict DFMC well because of its static nature; on the other hand LFMC deals with living organisms and the moisture content of such vegetation is much more dynamic and harder to model. The available models that are used to predict LFMC are often found to be lacking (Ruffault et al., 2018). Furthermore, LFMC observations are painstakingly collected by hand; not only does it require the researcher to travel into remote areas—often the most important areas in terms of wildfire risk—but they must also go through the long process of oven drying the samples. Moreover, this sampling cannot practically be used to create real-time predictions during fire season which rely on predictive models that in turn rely on being trained on these manual samples of LFMC.

The most prevalent models used for prediction of LFMC employ the use of meteorological indices and drought indices. It is found that these methods lead to somewhat useful results on a large scale, but when considered under a species or smaller scale spatial level, the models begin to fall apart with very high spatial variability (see table 7 taken from (Ruffault et al., 2018)). More recent approaches have begun to employ the use of remote sensing data with machine learning techniques to generate real-time predictions on a country level. These results are promising, but are once again susceptible to high spatial variability. Some studies have indicated that this spatial variability could be attributed to the fact that different species of vegetation react differently to the same weather conditions; some species can be considered high-responding, whose moisture content responds strongly to a change in weather, whereas others are low-responding. Research indicates that there is promise in using more mechanistic indices, especially as data on vegetation and vegetation distribution becomes better.

Our study investigates the viability of this mechanistic approach by combining meteorological factors, plant characteristics and remote sensing data. We focus our attention on the region of Southern California, an area of high wildfire risk, to prototype a model of this sort. Our model predicts the LFMC of nine different plant species scattered across Southern California using meteorological predictors (temperature, precipitation, relative humidity, solar radiation, and wind speed), NDVI, and various plant traits (specific leaf area, nitrogen per dry mass of leaf, phosphorous per dry mass of leaf, and plant height). A successful model would still depend on strong knowledge of the distribution of the vegetation within the area of concern, but this is outside the scope of this study. Apart from that, all of the predictors used are either readily available through automatic reporting or are features of vegetation that are common domain knowledge a priori, which conforms to the constraints of creating a model for real-time applications.

2. RELATED WORK

In (Ruffault et al., 2018), the authors assess and show that the prevailing method of using drought indices to predict LFMC is plagued by its limited ability for spatial predictability and cannot provide reliable estimates on a local level. The main benefit of using drought indices is that the data can be automatically sensed and is relatively widely available. An improvement on this method, as suggested by (Ruffault et al., 2018) is to use a more mechanistic approach. On the other hand, the authors in (Castro et al., 2003) illustrates that when considering a specific plant species, meteorological predictors are sufficient to be able to produce strong predictions (approximately 0.8 R^2) which are able to generalize to different locations and maintain its predictive ability. The limitation here is that if one seeks to create a model that could be generalized for large areas, one would need to get accurate estimates of the distribution of vegetative species. A helpful approach to ameliorate the uncertainty in the distribution of species is to take advantage of latent traits amongst species that could give us information on species we have not even sampled. For example, (?) points out that plants can be largely categorized into high and low responding categories indicating their moisture content responsiveness to drought.

Another new approach to predicting LFMC is a more deterministic approach that uses NDVI as a proxy for the moisture content. Furthermore, this can be combined with land surface temperature measurements which can also be inferred from remote sensing satellite data. This approach is detailed in (Chuvieco et al., 2004) using a physics based approach involving microwave backscatter. They are quite successful in obtaining strong predictions (R^2 of about 0.8 using just multiple linear regression). The model was based off of a similar dataset of LFMC samples in the Mediterranean, but are only specifically successful with a small number of shrub and grassland species. Similarly, (McCandless et al., 2020) uses remote sensing data, but with more flexible models on the WFAS dataset for the entire United States. The goal of this study was to create a real-time remote-sensing predictive model at the national level. This study primarily uses land surface temperature and satellite bands (which are used to derive NDVI) as predictors, and multiple linear regression, neural networks, random forest, and gradient boosted regression as models. It achieves an overall mean squared absolute error of about 20% which is approximately 25% of the standard deviation of LFMC, but there is no evaluation of the accuracy of the model at a small scale. Furthermore, the computational costs involved were significant, involving over 4 TB of data and the use of the US NCAR Casper cluster supercomputer.

These approaches have so far either been able to create large scale predictions that suffer from spatial variability at a small scale, or have been able to create strong predictions locally that do not necessarily generalize across all dimensions of the problem.

3. DATASET

In this study, we brought together four different datasets to predict the live fuel moisture content (LFMC) of vegetation in Southern California. The LFMC observations come from surface observations sampled manually. The meteorological data comes from automatic surface weather stations. The satellite data comes from the Landsat7 satellite. The plant characteristics come from the TRY plant database which is a curated conglomeration of many databases that largely involve manual sampling.

3.1 WFAS

Observations of LFMC content are provided by the USFS Wildfire Assessment System. This contains a national database of LFMC as well as dead fuel moisture content (DFMC) samples. LFMC is given by

$$\frac{WaterWeight}{OvenDriedWeight} \cdot 100$$

so it is possible for these values to be higher than 100. This study focuses on the Southern California subset of this data which contains a total of 37,912 total observations spanning 1982-05-06 to 2021-11-02. Although there are strong guidelines for the sampling of observations, the sampling is largely carried out by citizen scientists or volunteers. This means the observations may not be completely reliable, as well as the information on site location is approximate at best. We used reverse geocoding to find the nearest coordinates that the site names may indicate.

3.2 Meteorological Data

Meteorological data from automatic weather stations is often not consistent, and can contain many errors. Furthermore, databases such NOAA's Climate Data Online archives actually have large numbers of missing observations and many gaps and inconsistencies. One option was to use paid weather data services that generate interpolated data to fill in the gaps due to instrument errors, but this does not make sense for a study whose ultimate goal is real time prediction. In the end, we were able take advantage of Mesonet provided by Synoptic which is a third party that gathers and quality controls weather stations across the USA. The most reliable network for our region was the California Irrigation Management Information System. From this network we were restricted to retrieving only the most common weather variables that would assuredly be available in all of our stations. Furthermore, we only used weather stations that were at most 30km away from our geocoded WFAS site locations. The combination of this reduced our dataset to 7628 observations that we would consider. From the weather stations we used precipitation, wind speed, solar radiation, relative humidity, and temperature. The quality controlled weather stations only had a small number of missing observations as well as observations that were clear measurement errors[1]. For these missing variables we made a local imputation by taking the average of the five preceding observations under the assumption that the weather is most similar to what had just passed. All of these readings were provided hourly. Using these readings we could extracted features pertaining to the three, seven and fifteen day rolling average, maximum, and minimums for each of these five initial parameters[2].

3.3 TRY Plant Database

Vegetation specific characteristics were retrieved from the TRY Plant Trait Database which is a conglomeration of many datasets worldwide curated by a network of vegetation scientists. From this database we requested a long list of traits for our species of concern and trimmed this list down to four traits for relevance and data availability: nitrogen content per dry leaf area, phosphorous content per dry leaf area, plant height, and specific leaf area (a ratio of leaf area to leaf biomass). These characteristics were chosen for their relevance in conjunction with NDVI data under the hypothesis that different plants have different relationships between NDVI and moisture content, and this can be characterized by the properties of their leaves as well as their overall plant height which is not easily inferred by a satellite scan of NDVI[3].

3.4 Landsat 7

The Landsat 7 is a satellite that was put into orbit in 1999 with a 16 day orbit cycle. It detects 8 spectral bands from earth's surface. We collected data at each site location from the satellite for the range of dates available to us from the WFAS dataset. We calculate the Normalized Vegetation Index (NDVI), which is a measure of the density of live vegetation on land calculated by using the near infrared band and Red band: $\frac{NIR-RED}{NIR+RED}$. From each coordinate we took a 10km radius and calculated the mean NDVI to be consistent with the inherent uncertainty given by the the distances between observed LFMC and weather stations. Finally, we filtered out observations where there was too much cloud cover to get a reliable sattelite observation.

3.5 Data Processing

From the meteorological data, we were able to generate drought indices that have been widely used to predict fuel moisture content and in wildfire predictive indices such as the Canadian Forest Fire Weather Index. These include the Duff Moisture Code (DMC), the Drought Code (DC), and the Build up Index (BUI)[4]. We also generated a growth cycle variable based on the day of the year to capture the intrinsic plant cycle throughout the seasons based on the formula

$$D_t = \cos\left(\frac{2\pi t}{365} - 0.59\right)$$

from (Castro et al., 2003) where t is the day of the year. The initial meteorological features were further aggregated to produce for each variable (precipitation, humidity, temperature, wind speed, and solar radiation) their respective minimum, maximum and mean for the previous three, seven and fifteen days. Finally, we created interactions between the growth cycle and the meteorological variables to capture the different responses of plants to weather based on the phase of their growth cycle.

Due to the timing of satellite overflights from Landsat 7 (one observation every 16 days), NDVI data was not available on a daily basis. To adjust for NDVI not matching the target observation date we used an exponential decay function

$$ANDVI_t = \rho^{-h} \cdot NDVI_{t-h} \tag{1}$$

to downweight the importance of each observation. We set $\rho = 1.8$ to quickly decay in importance in the first 30 days. We then created interactions between our adjusted NDVI (ANDVI) and our vegetation characteristic variables to capture the hypothesis that ANDVI given the characteristics that generate ANDVI

[1] Anything outside of ranges: $0 < SolarRadiation < 1100w/m^2$; $0 < Precipitation < 100mm$; $0 < WindSpeed < 50km/hr$; $0 < RelativeHumidity < 100$; $-15 < Temp < 55C$ daily were considered as measurement errors based on the annual records of the area.

[2]

[3]

[4] See appendix for relevant formulas: DMC(formulas 8-13), DC(formulas **??**-6), and BUI(formula 14)

can be a proxy for fuel moisture content rather than just ANDVI alone. Furthermore, it is key to note that NDVI and NDVI related measures are included for their predictive value, but from an inference perspective it can only be viewed as a proxy of some latent unobservable characteristic of individual plant species that would also determine their LFMC.

We removed species Red Shank, Eastwoods Manzanita, and Brittlebrush from our study because these groups contained fewer than 25 observations each. This made them infeasible for splitting the data and having enough observations to make meaningful analysis on. We are left with nine plant types as seen in table 1. Our data contains $n = 6498$ observations and $p = 122$ variables; for certain fuels there are not that many more sample than parameters. Figure 1 shows the distribution of our target data and we can see that it is potentially lower bounded at some value. This is intuitive since when a plant is to dry dies.

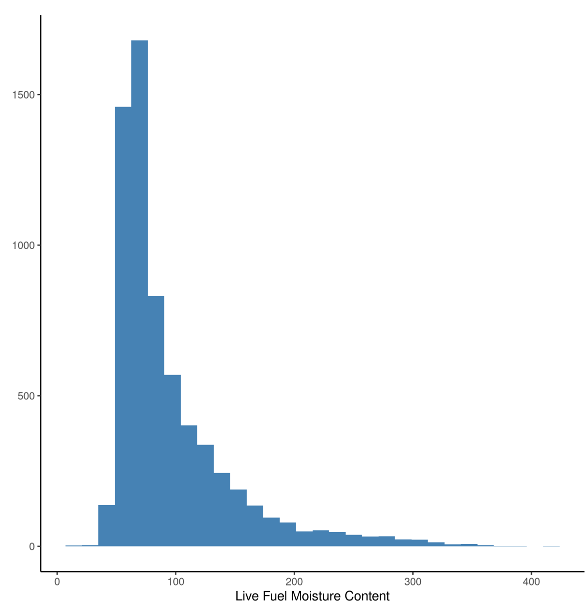

Fig. 1. Distribution of LFMC in our dataset

Plant Type	**N = 6,498**[1]
chamise	3,243 (50%)
chamise, new growth	1,071 (16%)
sage, black	557 (8.6%)
sagebrush, california	554 (8.5%)
sagebrush, black	421 (6.5%)
buckwheat, eastern mojave	205 (3.2%)
sage, purple	162 (2.5%)
ceanothus, bigpod	155 (2.4%)
ceanothus, hoaryleaf	130 (2.0%)

Table 1. Sample distribution across Fuels.

4. ANALYSIS

4.1 Bayesian Model Selection and Model Averaging

We will estimate the following basic regression model using Bayesian Methods.

$$y = \boldsymbol{\beta}^T \boldsymbol{X} + \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \rho I)$$

The priors we specify are as follows:

$$\begin{aligned} \boldsymbol{\beta} &\sim \mathcal{N}(0, ng\rho(\boldsymbol{X}^T\boldsymbol{X})^{-1}) \\ \rho &\sim IG(0.1, 0.1) \end{aligned}$$

which are standard priors for Bayesian regression. We simply set g to a default of $g = 1$, across all regressions we run.

Our covariate matrix contains all the variables mentioned in section 3. We avoid using LASSO because we have many highly correlated variables, and LASSO is known to behave badly in the presence of correlated variables—given two perfectly correlated variables, it to choose one to keep one and set the other to 0. We run a Bayesian Model Selection procedure, which samples from a posterior distribution of a *spike and slab* prior $\boldsymbol{\gamma} \in \{0, 1\}^p$. $\boldsymbol{\gamma}$ indicates which covariates are included in the model, i.e $\beta_j \neq 0$ if $\gamma_j = 1$. So if we set a prior on $\boldsymbol{\gamma}$ we can apply Bayes theorem and sample from $p(\boldsymbol{\gamma} \mid \mathbf{y})$, which allows us to find which models are most probable under the data. We set $\boldsymbol{\gamma} \sim$ BetaBinomial(1,1), which sets a uniform prior on model size. The posterior is estimated using MCMC in the `mombf` package[5].

First, we examine the marginal posterior probability that a variable is included in the model $p(\gamma_j = 1 \mid y)$. We run a set of unpooled regressions with model

[5]convergence checks verified that all our models converged

selection for every plant variable (refer to figures 8-11), which show the top 20 variables by marginal inclusion probability per plant. Examining these, we see that there are not too many similarities of highly probable variables between plant types as well as compared to the completely pooled model. For example, even though NDVI is high in the pooled analysis, it only has a significant marginal probability in a few of the plants, like *chamise, new growth* and *ceanothus, bigpod*. This suggests to us that different plant types are affected by different variables and there might not be some sparse number of variables that determine fuel moisture content for all plants.

We use Bayesian Model Averaging (BMA) to compute point estimates for our β coefficients. This gives the expected value of a coefficient over all possible models.

$$E[\boldsymbol{\beta} \mid \boldsymbol{y}] = \sum_{\gamma_j} E\left[\beta_j \mid \gamma_j = 1, \boldsymbol{y}\right] p(\gamma_j = 1 \mid \boldsymbol{y}).$$

It is worth noting that we are not too interested in the actual point estimates of the model. Since our focus is mostly on prediction, and the problem we are studying is much too complex to assume a simple causal structure. To naively interpret the coefficients as the marginal effect of a covariate on LFMC could be misleading, since we have not accounted for the effect of confounding variables—see (Westreich and Greenland, 2013) for a discussion.

The BMA point estimates for the completely pooled model are shown in table 6 for those variables with a high marginal probability, i.e those variables with a high probability of being contained in the true model. The interaction variables between the plant traits and NDVI are likely to be in the true model which highlights the importance of plant phenology in its fuel moisture content which has heretofore been overlooked as a predictor of LFMC. For example, the interaction between plant height and NDVI is around -4. This indicates that the influence of NDVI on LFMC is dependent on plant height. For smaller plants, low NDVI influences LFMC less than for taller plants. This lends credence to our approach of using plant traits to model LFMC, considering plant traits is informative as to how effective other variables are at predicting LFMC.

Figure 2 shows the BMA estimate for those variables which are the most likely in the completely pooled model. We can see that there is variation in the point estimate of variables between the plant types. We can see that many of the most likely variables in the pooled model are not a result of many plants having a high estimate for that one variable when comparing it to our unpooled models(the exception being Drought Code). This again brings us back to the suggestion that there is no small set of very important variables across groups—a possible sign that we are dealing with a non-sparse setting.

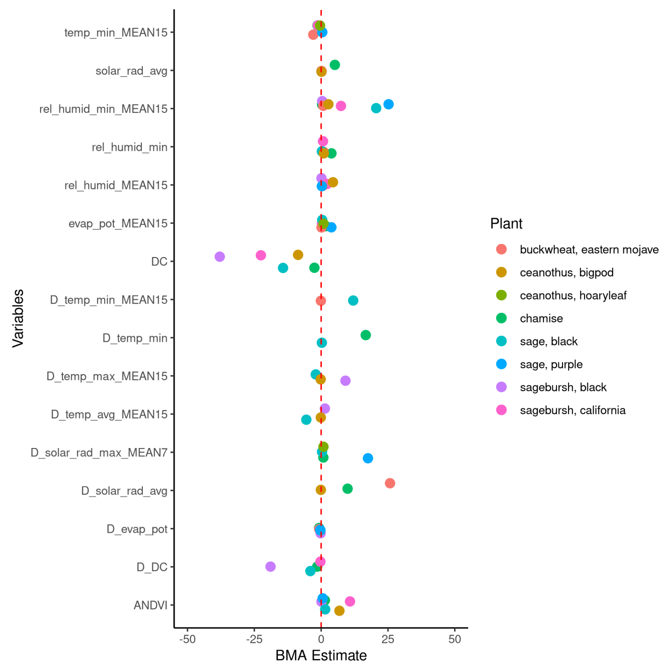

Fig. 2. Comparison of BMA estimates for the most probable variables in the completely pooled model grouped by plant type.

In this setting, specific coefficient interpretation should be treated with caution. There are can be pathological results that have non-intuitive interpretations. Though we note that interactions between plant traits and ANDVI is an effective predictor when looking at the whole model. Moreover, there is little commonality between the important predictors of LFMC between plant types.

4.2 Principal Components Analysis

Many of the meteorological variables are collinear with each other as is the nature of weather variables. We use PCA to reduce the dimensionality of the problem under the assumption that there are some smaller number of latent signals that drive weather patterns. Looking at the scree plot in figure 3 we can see that a significant amount of variation is described in the first component with the largest gap between component one and two. From this plot it appears that if there existed truly a latent variable signal structure, then it would consist of the first four to six components. Table 2 outline the makeup of the first six principal components. It is instructive to see that the principal components group our variables into intuitive clusters that could represent the true signals that are driving the variation in our data. These signals for the first six principal components can be largely categorized as seasonal temperature changes, relative humidity, wind speed, accumulated precipitation, NDVI's interaction with plant characteristics, and solar radiation.

PC1: Temperature	D_t, $D_t : T_{max15}$, $D_t : T_{mean15}$, $D_t : T_{max7}$, $D_t : T_{mean7}$, $D_t : T_{max3}$, $D_t : T_{mean3}$, $D_t : T$, $D_t : G_{max15}$
PC2: Humidity	H_{mean7}, H_{mean15}, H_{mean3}, H_{min7}, H_{min3}, H_{min15}, H, H_{min}, W_{max7}, W_{max15}
PC3: Wind	W_{mean7}, W_{mean3}, W_{mean15}, W_{max7}, W_{max3}, W_{max15}, W_{min7}, W_{min15}, W, W_{min3}, W_{max}
PC4: Precipitation	P_{mean7}, P_{Emean7}, P_{mean15}, $D_t : P_{Emean7}$, $P_{Emean15}$, $D_t : P_{mean7}$, P_{mean3}, P_{Emean3}, $D_t : P_{Emean15}$, $D_t : P_{Emean3}$
PC5: NDVI	$L_{phos} : A_{NDVI}$, A_{NDVI}, $L_{SLA} : A_{NDVI}$, $L_{nitro} : A_{NDVI}$, $V_{Height} : A_{NDVI}$, G_{mean3}, G_{max3}, T_{max3}, G_{max7}, G_{mean7}
PC6: Solar Radiation	G_{max3}, G_{max7}, G_{mean3}, G_{max}, G, G_{mean7}, D_{DC}, G_{max15}, G_{mean15}, B_{UI}

Table 2. The composition of the first six principal components including the ten most important variables for each component. We have given interpretations of the groupings on the left. See the appendix for a definition of each.

4.3 Mixed Effects Modelling

One strategy to combat the spatial variability that plagues many predictive models of LFMC would be to follow a more mechanistic approach that relies on characteristics of the vegetative species in question. These results could then be connected to the spatial dimension through estimating the distribution of the plants within each region; this portion is outside of

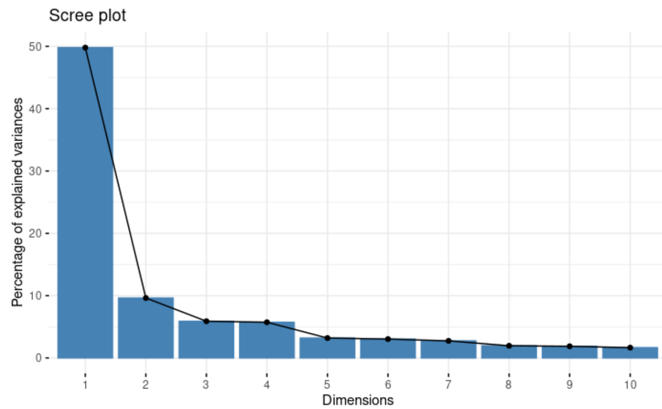

Fig. 3. The amount of explained variance for each of the first 10 principal components. See table 8.

the scope of this study. Without a strong model and data that can predict LFMC from some unknown characteristics, we will take these characteristics as latent variables and use a mixed effects model to account for and learn from these variables. We will generate a model both using principal components and using variables selected from Bayesian Model Selection from the general model given by equation:
2.

$$
\begin{aligned}
\mathrm{LFMC}_i &\sim \mathcal{N}\left(\mu, \sigma^2\right) \\
\mu &= \alpha_{j[i]} + \gamma X_0 + \beta_{j[i]} X_1 \\
\begin{bmatrix} \alpha_j \\ \beta_j \end{bmatrix} &\sim \mathcal{N}\left(\begin{bmatrix} \mu_{\alpha_j} \\ \mu_{\beta_j} \end{bmatrix}, \ \Sigma \right), \text{for Species j} = 1, \dots 9
\end{aligned} \tag{2}
$$

LFMC is modelled under a normal distribution with mean μ and variance σ^2 whose mean parameter is estimated from a mixture of Gaussian distributions composed of three parts. The first part is the intercept for each group given by α_j. The second part is given by the fixed effects with coefficients γ and X_0 which represents relevant partition of the design matrix. The third part is given by the rest of the design matrix of the predictors used as random effects with group coefficients given by β_j. Finally, α_j's and β_j's are estimated by a normal distribution with mean $\mu_{\alpha_j - \beta_j}$ and covariance Σ.

For the PCA-based model we use the first twenty two principal components as predictors; these explain 95% of the cumulative variance. We first fit two baseline models: a completely pooled OLS and a completely unpooled OLS. We then fit a model varying the intercepts. In this case in reference to model 2 this would mean that X_0 is the entire design matrix of all predictors. Next we fit a model using all components as random effects; i.e. X_1 is the entire design matrix. We then fitted a model using just the first six principal components for X_1 and the other 16 in X_0; we choose these components through a combination of observing the scree plot (fig 3) and observing that the first six components still explains nearly 80% of the cumulative variance. After fitting this model, we run ANOVA tests (table 12) to determine if all the components are truly significant as a random effect. Under its recommendation we fit a final model using only principal components 1, 2, 3, 5, and 6[6].

For the BMS-based model we use the 54 predictors chosen heuristically from our Bayesian model selection analysis and follow a similar approach. We make similar baseline models as well as a varying intercept model. Due to issues of collinearity amongst the random effects, we cannot use all the predictors that we heuristically chose from our analysis of the marginal posterior probabilities of inclusion. We further trim our choice of predictors by considering their correlations and setting a threshold of 0.9. Finally, we fit a model using eleven predictors: H_{mean7}, D_{DC}, T_{min15}, W_{mean15}, $D : D_{DMC}$, $D : W_{max}$, H, G_{max3}, G_{max}, and $L_{nitro} : A_{NDVI}$ to compose X_1. Using the same ANOVA tests (table 11), we remove H, G_{max3}, G_{max}, and $L_{nitro} : A_{NDVI}$ for a minimal model of 6 random effects.

Comparing the mixed effect models based on the deviance information criterion (DIC) in table 3, the best model is the PCA-based model that uses all the principal components with a DIC of 49,607 and deviance 49,596, but BMS-based model that uses eleven varying slopes is not that much worse with a DIC of 49,783 and deviance 49,634. Although the BMS model uses fewer random effects, it has a higher number of effective parameters implied by the difference between the DIC and deviance. These models also perform similarly in prediction with out of sample R^2 of approximately 0.68.

We tested the predictive accuracy of our models on a held out sample and measure the overall R^2 as well as the species specific R^2. For our mixed effect models we make one thousand bootstrap simulated predictions[7]. We make simple predictions with 95% confidence intervals with our OLS models. Figures 4 and 5 show that our models can both successfully improve model predictive accuracy as well as reduce the variation between groups. These figures outline the different predictive abilities of the different models using the same base predictors as specified above. By grouping the predictions in the same way for each model, stratified by each individual species group, we can see the ability of the mixed effects models to learn information across groups. In figure 4 it is evident that the baseline OLS models have a relatively high dispersion of predictive abilities across species, and the mixed effects models are able to learn information across groups and significantly increase the predictions of species such as Black Sage, Eastern Mojave Buckwheat, Chamise, and Chamise New Growth. These species would likely have been characterized as "low-responding" species by (Ruffault et al., 2018). There is a large disparity in the number of observations for each species ranging from a hundred to a few thousand. In this case, we might infer that Eastern Mojave Buckwheat and Black Sage, which had only 206 and 421 observations, benefited in this regard by taking advantage of the grand mean of all groups and pooling towards it. But, the same cannot be said of Chamise, and Chamise New Growth, which have 3,251 and 1,073 observations respectively. Together they make up for nearly two thirds of all observations in this sample. For these two groups we can observe a large improvement from the completely pooled OLS and the completely unpooled OLS predictions which indicates that there are species specific traits that are not accounted for by the predictors. Further improvement is only then achieved significantly when random slopes are incorporated, showing that different species react differently to different predictors, and by characterizing this we can more accurately describe the data. This regularization is effective and useful for both large and small group sizes meaning that the improvements in the global predictive ability is not solely derived from regularizing the groups with small sample sizes[8]. In the BMS-based models

[6] This model is referred to as the PC min model in the rest of this paper.

[7] The predictInterval function was used from merTools which differs from the standard arm::sim by incorporating the uncertainty in the variance of the group parameters by making a few draws of these variances while still treating them as 'fixed'. This leads to a higher prediction interval than `arm::sim` which only incorporates the uncertainty of the fixed effects and the observation level variances and of course is higher than expected confidence intervals of OLS predictions by nature.

[8] The appendix contains summary tables of the random effects and estimated coefficients to see the precise changes in estimated coefficients between such models as OLS and the different random

Models	Deviance	DIC	OOS R^2
PCA - Varying Intercept	51438	52437.8	0.5463
PCA - Varying Intercept + 22 PCs	49595.5	49606.9	0.6846
PCA - Varying Intercept + 6 PCs	50088.5	50089.7	0.6696
PCA - Varying Intercept + 5 PCs	50160.3	510158.4	0.6582
BMS - Varying Intercept	50891.5	51808.8	0.5961
BMS - Varying Intercept + 11 Slopes	49634.3	49783.2	0.6880
BMS - Varying Intercept + 6 Slopes	49690.2	49850	0.6802

Table 3. A comparison of mixed effect models' deviance, DIC and out of sample R^2. The PCA models indicate the number of first principal components used as random effects, with the exception that '5 PCs' uses principal components 1, 2, 3, 5, and 6 chosen based on ANOVA tests. The simplest BMS model uses: H_{mean7}, D_{DC}, T_{min15}, W_{mean15}, $D : D_{DMC}$, $D : W_{max}$; and the larger model adds on: H, G_{max3}, G_{max}, $L_{nitro} : A_{NDVI}$.

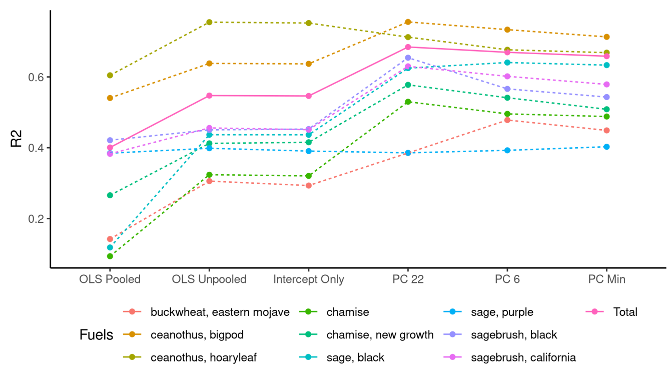

Fig. 4. Predictive accuracy of different models using the first twenty two principal components as predictors. See table 10 for full results.

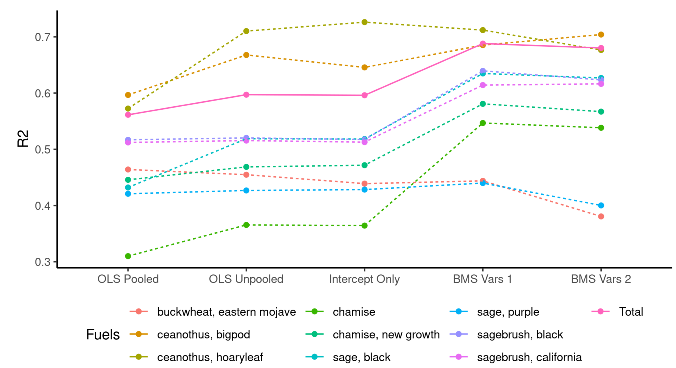

Fig. 5. Predictive accuracy of different models using predictors selected using Bayesian model selection. See table 9 for full results.

(fig 5) a similar story holds for Chamise and Chamise, New Growth, albeit less drastic.

Figure 7 compares the OLS unpooled estimates and our PCA-based model for Black Sage, one of the species that saw the most drastic improvement. We can observe that the prediction intervals are much greater than the OLS confidence intervals. But, in the end, the bootstrapped mean predictions can be seen to be better than the OLS estimates, especially for the values that are below the 79% threshold which is a critical threshold for wildfire predictions (Dennison and Moritz, 2009). We notice that some of our prediction intervals fall below zero, which indicates an area of improvement on this model since it is impossible for a plant's LFMC to be below zero.

effects models

Comparing the predictions using the best BMS and PCA based models for Chamise in figure 6, there is not a huge difference in their predictions nor their predictive intervals. This is further evident in the residual unexplained variance at the observation level of these models; for the PCA model it is 795.2, and for the BMS model it is 809.8. Although the BMS model's predictors could be a bit easier to interpret, intuitively the view that a small number of signals are responsible for the large number of predictors that forms the basis of principal components analysis aligns with the types of predictors and the way they are generated in this model. It also then makes sense that the predictors chosen through BMS include predictors in all categories (temperature, precipitation, humidity, solar radiation, NDVI, and drought indices), indicating that BMS is able to select these predictors from amongst an environment of collinearity, but these might not necessarily be the true determinants of LFMC.

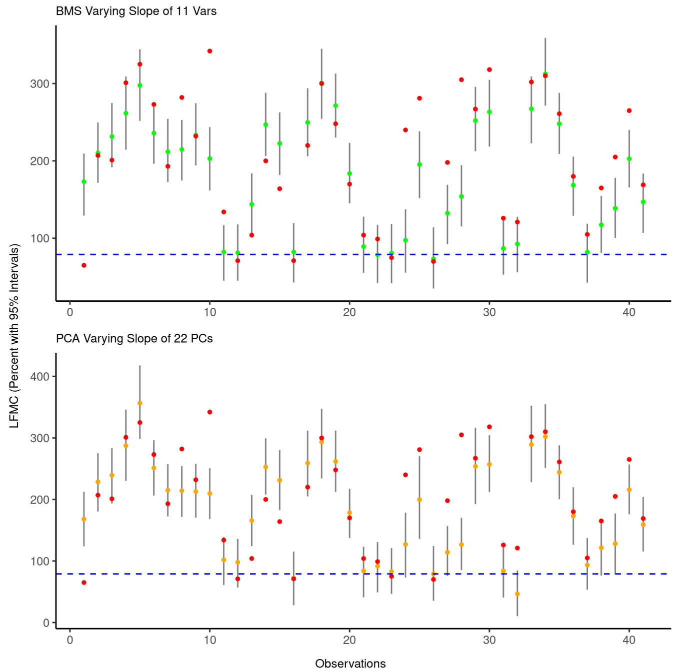

Fig. 6. Out of sample predictions of Black Sage using unpooled OLS and mixed effects model using all 22 principal components as predictors. The red points indicate the true values and the blue dotted line indicates LFMC=79%. Prediction intervals for the mixed effects model and confidence intervals for OLS are shown for the 95% level.

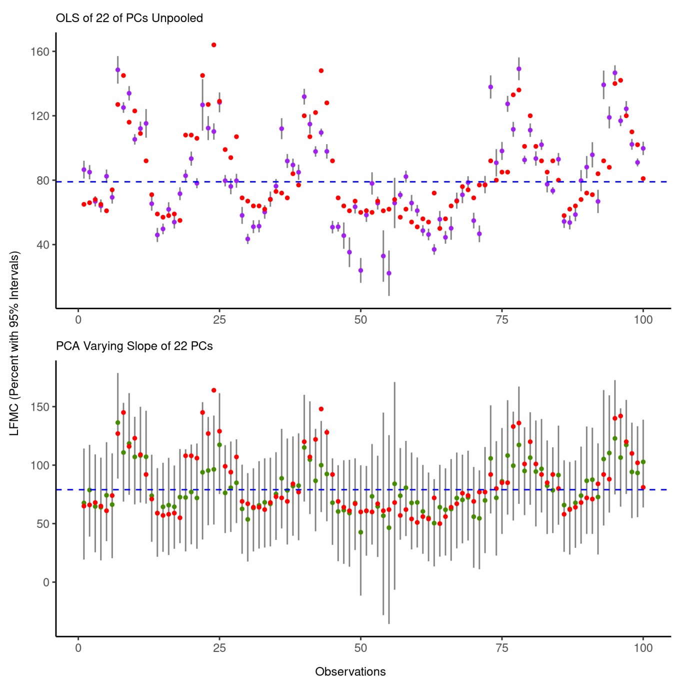

Fig. 7. Out of sample predictions for the first 100 observations of Chamise using a PCA-based mixed effects model and a BMS-based mixed effects model. The red points indicate the true values and the blue dotted line indicates LFMC=79%. Prediction intervals for the mixed effects model and confidence intervals for OLS are shown for the 95% level.

5. DISCUSSION

The Bayesian Model Selection was not particularly illuminating, but gave us hints about the structure of the setting we are studying—namely that sparsity is not a particularly likely state of affairs. This is because there is not much commonality between important covariates in the unpooled between-plant analysis. This motivates the approach taken in section 4.3 and beyond where we estimate a mixed effects model informed by Bayesian Model Selection—where we are able to relax the assumption that the effect of a covariate is identical across plants.

Mixed effects models here are an effective way to deal with the dispersion of predictive ability amongst groups of plant species. They provide stronger predictive results and also insights into the different responses of different species that determine their LFMC. There are a few ways in which these models can be improved and extended to provide a more complete picture. Firstly, given more computing resources, it would be possible to perform a more rigorous search of our predictor space for the predictors that can capture the most variance between groups. Moreover, it would be an improvement to run hierarchical models to encode prior domain knowledge. This would include a sensible lower bound to LFMC since living plants have a definite lower bound. As seen in the predictions in figure 7, this lower bound was violated. Another way to encode prior beliefs would be to employ quantile regression within a mixed effects model. Since this model, is motivated to improve wildfire prediction models and we know that the 79% threshold of LFMC is a critical threshold (Dennison and Moritz, 2009), we could use quantile regression to upweight the importance of these lower observations and downweight the heavy tails in the other direction; we are more interested that vegetation is too dry rather than over saturated. This would be a cleaner way than the use of logistic regression in (Ruffault et al., 2018).

Further work can also be done by gathering more data. Gathering more LFMC data in a significant way may not be feasible, but gathering more accurately matched meteorological and NDVI data is. This would allow the model to be expanded to find other groupings by including more groups of species as well as to have enough observations to consider the time and spatial dimensions. Firstly, if more species could be included, then there are possibilities of using clustering techniques to discover latent clusterings of the species that could be distinct from the current prevalent groupings: by species, as low and high responding species, or by type (i.e. shrub or tree). As we saw in figure 4, the predictability of certain species was not solely due to a low sample size. Finally, with more observations it would be prudent to find ways to learn more from the data via time and spatial dimensions such as through time series techniques and spatial regression.

6. APPENDIX

6.1 Code

All source code can be found at https://github.com/antotocar34/fmc_prediction

The main code for analysis is in https://github.com/antotocar34/fmc_prediction/tree/master/code/analysis/main

6.2 Variable Name Definitions

The symbolic representation of our parameters is indicated below. Items 1 - 5 take use subscripts combining 'min', 'mean', or 'max' with 3, 7, or 15 which indicates the aggregation performed over the previous number of days. I.e. P_{max7} indicates the maximum daily accumulated precipitation that occurred in the last seven days.

1. P - Accumulated Precipitation
   - *eff* - Effective Precipitation
2. G - Solar Radiation
3. T - Temperature
4. H - Relative Humidity
5. W - Wind Speed
6. E - Potential Evapotranspiration
7. D - Indices
   - t - Growth Cycle Indicator
   - DC - Drought Code
   - DMC - Duff Moisture Code
8. L - Leaf Characteristics
   - *phos* - Phosphorous per dry mass of leaf
   - *nitro* - Nitrogen per dry mass of leaf
   - *SLA* - Specific Leaf Area
9. V_{height} - Vegetation Height
10. B_{UI} - Build up Index
11. A_{NDVI} - Adjusted NDVI

6.3 Formulas

Drought Code

$$DC = \begin{cases} DC_{t-1} + 0.5 \cdot V & \text{for } P \leq 2.8 \\ DC_{r_t} + -.5 \cdot V & \text{for } P > 2.8 \end{cases} \tag{3}$$

Where DC_{t-1} is the previous day's value, and if unavailable is set to 15 and V is the potential evapotranspiration calculated by:

$$V = 0.36 \cdot (T_{12} + 2.8) + L_f \tag{4}$$

Where T_{12} is the temperature recorded at noon if $T_{12} \geq -2.8$ and otherwise $T_{12} = -2.8$ and L_f is a day-length factor given by Table 4

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
-1.6	-1.6	-1.6	0.9	3.8	5.8	6.4	5.0	2.4	0.4	-1.6	-1.6

Table 4. Day length factor for the drought code

And DC_{r_t} is calculated by first calculating effective precipitation P_{eff} using precipitation P:

$$P_{eff} = 0.83 \cdot P - 1.27 \tag{5}$$

Then calculating the day's moisture equivalent after rain Q_{r_t}:

$$Q_{r_t} = 800 \cdot e^{\frac{-DC_{t-1}}{400}} + 3.937 \cdot P_d \tag{6}$$

And finally calculating DC_{r_t}. Note if $DC_{r_t} < 0$ then $DC_{r_t} = 0$:

$$DC_{r_t} = 400 \cdot \ln \frac{800}{Q_{r_t}} \tag{7}$$

Duff Moisture Code

$$DMC_t = \begin{cases} DMC_{t-1} + 100 \cdot K & \text{for} P \leq 1.5 \\ DMC_{r_t} + 100 \cdot K & \text{for} P > 1,5 \end{cases} \tag{8}$$

Where DMC_{t-1} is the previous day's DMC or 6 if unavailable, K is the log drying rate calculated by using the temperature recorded at noon, T_{12} if $T_{12} \geq -1.1$ otherwise $T_{12} = -1.1$ and the relative humidity in percent recorded at noon H_{12} and the effective day length L_e given by 5

$$K = 1.894 \cdot (T_{12} + 1.1) \cdot (100 - H_{12}) \cdot L_e \cdot 10^{-6} \tag{9}$$

And DMC_{r_t} is calculated by first calculating effective rainfall P_e using precipitation P:

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
6.5	7.5	9.0	12.8	13.9	13.9	12.4	10.9	9.4	8.0	7.0	6.0

Table 5. Effective day length for duff moisture code

$$P_e = 0.92 \cdot P - 1.27 \tag{10}$$

Then calculating the duff moisture content M_{r_t}:

$$M_{r_t} = 20 + e^{5.6348 - \frac{DMC_{t-1}}{43.43}} + \frac{1000 \cdot Pe}{48.77 + b \cdot P_e} \tag{11}$$

Where b is calculated by:

$$b = \begin{cases} \frac{100}{0.5 + 0.3 \cdot DMC_{t-1}} & , \text{for} DMC_{t-1} \leq 33 \\ 14 - 1.3 \ln(DMC_{t-1}) & , \text{for} 33 < DMC_{t-1} \leq 65 \\ 6.2 \cdot \ln(DMC_{t-1}) - 17.2 & . \text{for} DMC_{t-1} > 65 \end{cases} \tag{12}$$

And finally:

$$DMC_{r_t} = 244.72 - 43.43 \cdot \ln(M_{r_t} - 20), \text{if} DMC_{r_t} < 0 \text{then} DMC_{r_t} = 0 \tag{13}$$

Build Up Index

$$BUI = \begin{cases} 0.8 \cdot \frac{DMC \cdot DC}{DMC + 0.4 \cdot DC} & \text{for } DMC \leq 0.4 \cdot DC \\ DMC - (1 - \frac{0.8 \cdot DC}{DMC + 0.4 \cdot DC}) \cdot [0.92 + (0.0114 \cdot DC)^{1.7}] & \text{for } DMC > 0.4 \cdot DC \end{cases} \tag{14}$$

6.4 Tables

	BMA Estimate	2.5%	97.5%	$p(\cdot \mid \gamma)$
Station Elevation	-3.370478	-5.127001	-1.613143	0.9999536
G	6.350300	4.102470	8.593709	0.9807483
H_{min}	4.750553	2.585580	7.093371	0.9960038
D_{DC}	-8.478542	-11.477374	-6.585258	1.0000000
G_{max7}	8.338130	0.000000	12.918999	0.8532256
H_{min}	16.044091	9.492875	22.604520	0.9999944
H	-9.780191	-16.890643	-2.822964	0.9954583
T_{min}	-8.613416	-14.058442	-3.061096	0.9930988
E	19.613844	14.465487	24.875580	0.9941110
$D \cdot G_{avg15}$	13.535149	8.116125	19.126382	0.9785908
$D \cdot T_{min15}$	20.573545	13.743946	33.975686	0.9871351
$D \cdot E$	-18.391673	-25.613727	-10.672422	0.9848089
$D \cdot D_{DC}$	-4.055092	-6.317401	-1.682868	0.9774863
$D \cdot G_{max7}$	32.617237	22.700637	41.218592	0.9597782
$D \cdot W_{max}$	-26.134160	-40.647366	0.000000	0.8690481
$D \cdot T_{max}$	-152.708005	-204.046987	-106.004539	1.0000000
$D \cdot T_{min}$	-54.003196	-69.996789	-38.484842	0.9678281
$D \cdot T_{avg}$	183.904898	168.929414	209.749593	0.9999964
A_{NDVI}	-28.178194	-30.559631	-25.766596	1.0000000
$L_{nitro} \cdot A_{NDVI}$	16.067462	14.192315	17.920441	1.0000000
$L_{phos} \cdot A_{NDVI}$	36.670841	34.630477	38.768370	1.0000000
$V_{height} \cdot A_{NDVI}$	-4.468335	-5.291190	-3.646047	0.9998859
$SLA \cdot A_{NDVI}$	-10.777184	-11.517194	-10.067203	1.0000000

Table 6. BMA estimates of variables with a high marginal inclusion probability.

Drought Indices Predictive Accuracy

		DC			DMC			KBDI		
Species	Site	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
Cistus albidus	D06S3	0.52	17.2	13.3	0.57	16.2	12.9	0.46	18.2	13.9
Cistus albidus	D30S2	0.47	18.1	13.9	0.42	18.9	15.4	0.36	19.9	15.2
Cistus albidus	D34S2	0.50	14.4	11.3	0.47	14.8	11.8	0.37	16.1	12.4
Cistus albidus	D83S2	0.64	12.8	9.5	0.25	18.3	15.4	0.62	13.1	9.8
Cistus albidus	D83S3	0.39	17.7	13.9	0.18	20.4	16.7	0.41	17.4	13.6
Cistus mon	D06S2	0.45	20.2	15.8	0.50	19.4	15.3	0.41	21.0	15.7
Cistus mon	D11S2	0.32	16.0	13.0	0.29	16.3	13.1	0.24	16.8	13.5
Cistus mon	D2AS1	0.47	18.5	14.9	0.38	20.1	16.3	0.34	20.7	16.1
Cistus mon	D2BS2	0.08	23.4	18.9	0.23	21.4	17.1	0.06	23.7	19.1
Cistus mon	D2BS3	0.18	21.1	17.2	0.42	17.7	14.4	0.19	21.0	17.0
Cistus mon	D66S1	0.15	23.8	18.7	0.47	18.8	14.7	0.04	25.4	20.3
Cistus mon	D66S2	0.29	22.5	18.8	0.38	21.1	17.5	0.22	23.6	19.4
Cistus mon	D83S1	0.48	17.4	12.8	0.27	20.5	16.4	0.44	18.0	13.1
Cistus mon	D83S3	0.42	20.0	16.0	0.27	22.5	18.6	0.43	19.9	15.7
Erica arborea	D2AS1	0.48	13.7	10.2	0.18	17.1	12.5	0.37	15.0	11.1
Erica arborea	D2AS2	0.51	11.1	8.8	0.45	11.7	8.9	0.47	11.6	9.2
Erica arborea	D2BS2	0.34	12.1	9.0	0.17	13.6	10.0	0.33	12.2	9.2
Erica arborea	D2BS3	0.49	10.5	8.6	0.32	12.1	9.9	0.45	10.9	8.7
Erica arborea	D66S1	0.43	11.0	8.8	0.25	12.6	9.9	0.30	12.1	9.6
Erica arborea	D83S1	0.61	11.2	8.8	0.10	17.1	13.6	0.54	12.2	9.8
Quercus coccifera	D11S1	0.29	5.8	4.6	0.05	6.7	5.3	0.24	6.0	4.7
Quercus coccifera	D13S1	0.40	6.5	4.7	0.10	8.0	6.1	0.36	6.7	4.9
Quercus coccifera	D13S2	0.36	6.2	4.5	0.09	7.4	5.8	0.37	6.2	4.5
Quercus coccifera	D34S2	0.42	5.7	4.3	0.06	7.3	5.8	0.47	5.5	4.2
Quercus coccifera	D84S1	0.54	4.4	3.4	0.10	6.2	4.8	0.56	4.3	3.3
Quercus ilex	D30S2	0.40	6.2	4.8	0.12	7.5	6.0	0.37	6.3	5.0
Quercus ilex	D83S2	0.43	4.2	3.3	0.06	5.4	4.3	0.45	4.1	3.3
Quercus ilex	D84S1	0.56	4.5	3.6	0.06	6.6	5.4	0.61	4.3	3.4
Quercus ilex	D84S2	0.51	6.6	4.7	0.23	8.2	6.6	0.42	7.1	5.1
Rosmarinus off	D06S1	0.67	16.5	13.2	0.58	18.4	14.8	0.61	17.8	14.0
Rosmarinus off	D11S1	0.46	16.8	13.9	0.39	17.9	14.5	0.39	17.9	14.9
Rosmarinus off	D13S1	0.41	18.7	15.3	0.50	17.1	13.6	0.26	20.9	17.0
Rosmarinus off	D13S2	0.47	14.7	11.2	0.45	15.0	12.1	0.32	16.7	12.8
Rosmarinus off	D84S2	0.45	24.4	20.2	0.60	20.7	16.1	0.31	27.2	23.2

Table 7. The predictive abilities of different drought indices when broken down by site and species as detailed by (Ruffault et al., 2018)

PCA Summary

	Standard deviation	Proportion of Variance	Cumulative Proportion
PC1	7.633	0.498	0.498
PC2	3.354	0.096	0.594
PC3	2.625	0.059	0.653
PC4	2.588	0.057	0.710
PC5	1.932	0.032	0.742
PC6	1.881	0.030	0.772
PC7	1.790	0.027	0.800
PC8	1.510	0.020	0.819
PC9	1.480	0.019	0.838
PC10	1.389	0.016	0.855
PC11	1.261	0.014	0.868
PC12	1.247	0.013	0.881
PC13	1.206	0.012	0.894
PC14	1.064	0.010	0.904
PC15	1.031	0.009	0.913
PC16	0.986	0.008	0.921
PC17	0.909	0.007	0.928
PC18	0.860	0.006	0.934
PC19	0.821	0.006	0.940
PC20	0.757	0.005	0.945
PC21	0.739	0.005	0.950
PC22	0.721	0.004	0.954

Table 8. Summary of the PCA analysis.

Model Predictive Accuracy

	Fuels	OLS Pooled	OLS Unpooled	Intercept Only	BMS Vars 1	BMS Vars 2
1	buckwheat, eastern mojave	0.464	0.455	0.439	0.444	0.381
2	ceanothus, bigpod	0.597	0.668	0.646	0.685	0.704
3	ceanothus, hoaryleaf	0.572	0.710	0.726	0.712	0.677
4	chamise	0.310	0.365	0.364	0.547	0.538
5	chamise, new growth	0.446	0.469	0.472	0.581	0.567
6	sage, black	0.432	0.519	0.518	0.635	0.627
7	sage, purple	0.421	0.427	0.428	0.440	0.400
8	sagebrush, black	0.517	0.520	0.517	0.639	0.623
9	sagebrush, california	0.512	0.516	0.513	0.614	0.616
10	Total	0.561	0.597	0.596	0.688	0.680

Table 9. The out of sample R^2s for each group of fuels after running different models on the features chosen by Bayesian Model Selection.

	Fuels	OLS Pooled	OLS Unpooled	Intercept Only	PC 22	PC 6	PC Min
1	buckwheat, eastern mojave	0.142	0.306	0.293	0.385	0.478	0.449
2	ceanothus, bigpod	0.541	0.638	0.637	0.756	0.734	0.713
3	ceanothus, hoaryleaf	0.605	0.755	0.752	0.713	0.677	0.669
4	chamise	0.093	0.324	0.320	0.530	0.496	0.488
5	chamise, new growth	0.266	0.412	0.415	0.578	0.541	0.509
6	sage, black	0.118	0.437	0.437	0.625	0.641	0.633
7	sage, purple	0.385	0.399	0.391	0.386	0.393	0.403
8	sagebrush, black	0.421	0.450	0.453	0.654	0.566	0.543
9	sagebrush, california	0.383	0.456	0.451	0.630	0.602	0.579
10	Total	0.401	0.547	0.546	0.685	0.670	0.659

Table 10. The out of sample R^2s for each group of fuels after running different models on the first twenty two principal components which account for 95% of the cumulative variance as determined by PCA.

ANOVA Tests

Feature	npar	$\log p(\mathbf{y} \mid \mathbf{x})$	AIC	LRT	Df	Pr(>Chisq)
	134	$-\$24,711.260$	$49,690.530$			
H	122	$-24,717.170$	$49,678.340$	11.811	12	0.461
H_{mean7}	122	$-24,736.930$	$49,717.860$	51.330	12	0.00000
G_{max3}	122	$-24,713.740$	$49,671.470$	4.948	12	0.960
D_{DC}	122	$24,848.630$	$-49,941.270$	274.739	12	0
T_{min15}	122	$-24,733.510$	$49,711.030$	44.500	12	0.00001
W_{mean15}	122	$-24,731.650$	$49,707.290$	40.763	12	0.0001
$D : D_{DMC}$	122	$-24,726.060$	$-49,696.130$	29.604	12	0.003
$L_{nitro} : A_{NDVI}$	122	$-24,715.640$	$49,675.280$	8.748	12	0.724
$D : W_{max}$	122	$-24,755.600$	$49,755.210$	88.682	12	0
G_{max}	122	$-24,714.980$	$49,673.960$	7.428	12	0.828
$D : H$	122	$-24,718.760$	$49,681.520$	14.994	12	0.242

Table 11. Here we show the results of using ANOVA to test for single term deletions for the BMS based mixed effects models that chooses 11 different varying slopes. Evidently here, the ANOVA tests suggest the eletion of H, G_{max3}, $L_{nitro} : A_{NDVI}$, G_{max}, and $D : H$.

Principal Component	npar	Likelihood	AIC	LRT	df	$P(>\chi^2_{df})$
	52	$-25,043.690$	$50,191.380$			
1	45	$-25,537.270$	$51,164.540$	987.165	7	0
2	45	$-25,078.580$	$50,247.160$	69.785	7	0
3	45	$-25,128.690$	$50,347.380$	170.005	7	0
4	45	$-25,047.710$	$50,185.420$	8.041	7	0.329
5	45	$-25,069.010$	$50,228.010$	50.636	7	0
6	45	$-25,091.280$	$50,272.560$	95.180	7	0

Table 12. Here we show the results of using ANOVA to test for single term deletions for the PCA based mixed effects models that chooses the first six principle components of 22 as varying slopes. The first column indicates the term that was tested for deletion. The ANOVA tests here suggest the removal of the 4th principle component.

6.5 Marginal Probability Per Plant

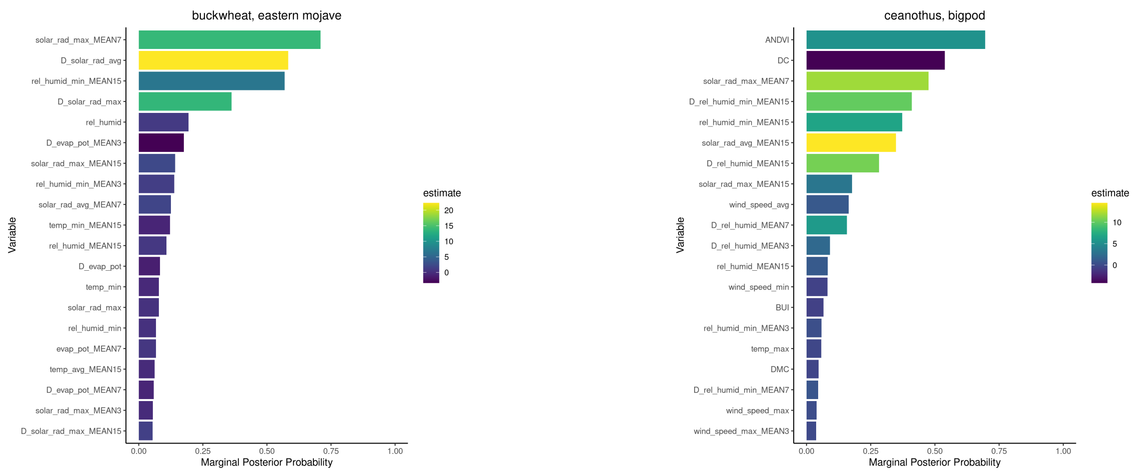

Fig. 8.

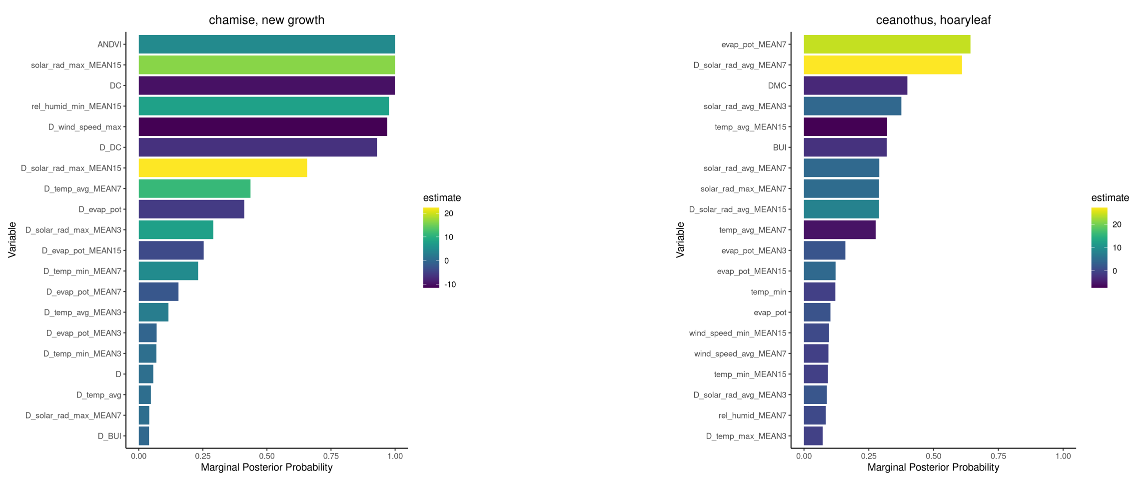

Fig. 9.

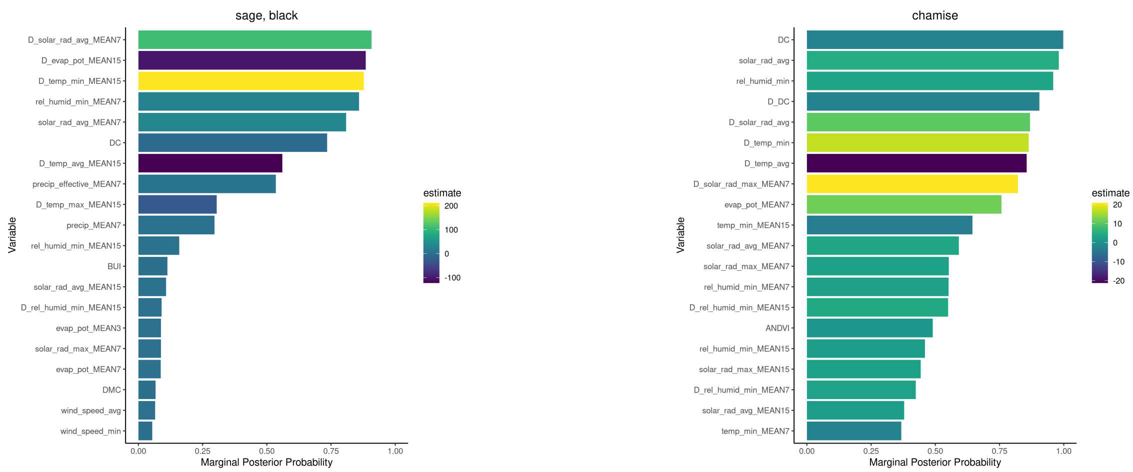
sage, black
D_solar_rad_avg_MEAN7
D_evap_pot_MEAN15
D_temp_min_MEAN15
rel_humid_min_MEAN7
solar_rad_avg_MEAN7
DC
D_temp_avg_MEAN15
precip_effective_MEAN7
D_temp_max_MEAN15
precip_MEAN7
rel_humid_min_MEAN15
BUI
solar_rad_avg_MEAN15
D_rel_humid_min_MEAN15
evap_pot_MEAN3
solar_rad_max_MEAN7
evap_pot_MEAN7
DMC
wind_speed_avg
wind_speed_min
Variable
Marginal Posterior Probability
0.00 0.25 0.50 0.75 1.00
estimate
200
100
0
-100
chamise
DC
solar_rad_avg
rel_humid_min
D_DC
D_solar_rad_avg
D_temp_min
D_temp_avg
D_solar_rad_max_MEAN7
evap_pot_MEAN7
temp_min_MEAN15
solar_rad_avg_MEAN7
solar_rad_max_MEAN7
rel_humid_min_MEAN7
D_rel_humid_min_MEAN15
ANDVI
rel_humid_min_MEAN15
solar_rad_max_MEAN15
D_rel_humid_min_MEAN7
solar_rad_avg_MEAN15
temp_min_MEAN7
Variable
Marginal Posterior Probability
0.00 0.25 0.50 0.75 1.00
estimate
20
10
0
-10
-20

Fig. 10.

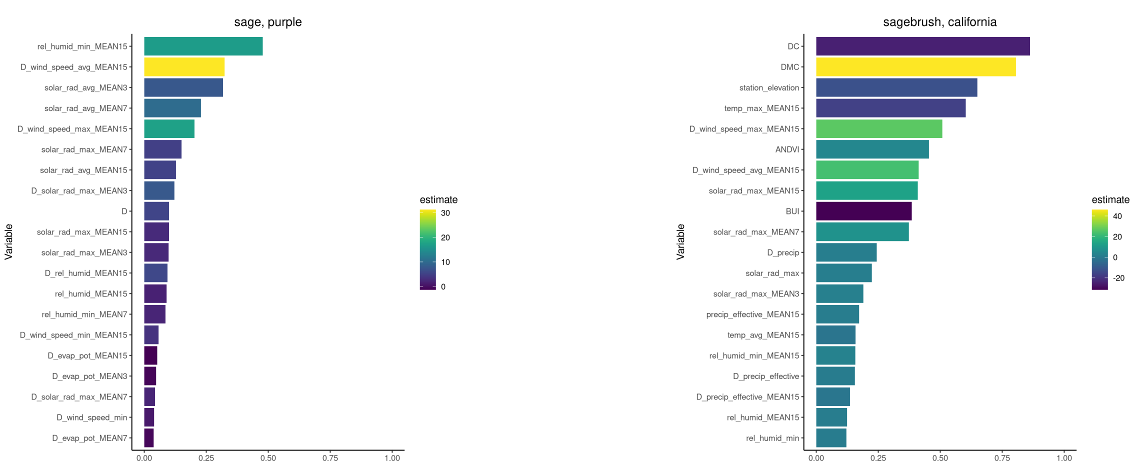
sage, purple
rel_humid_min_MEAN15
D_wind_speed_avg_MEAN15
solar_rad_avg_MEAN3
solar_rad_avg_MEAN7
D_wind_speed_max_MEAN15
solar_rad_max_MEAN7
solar_rad_avg_MEAN15
D_solar_rad_max_MEAN3
D
solar_rad_max_MEAN15
solar_rad_max_MEAN3
D_rel_humid_MEAN15
rel_humid_MEAN15
rel_humid_min_MEAN7
D_wind_speed_min_MEAN15
D_evap_pot_MEAN15
D_evap_pot_MEAN3
D_solar_rad_max_MEAN7
D_wind_speed_min
D_evap_pot_MEAN7
Variable
Marginal Posterior Probability
0.00 0.25 0.50 0.75 1.00
estimate
30
20
10
0
sagebrush, california
DC
DMC
station_elevation
temp_max_MEAN15
D_wind_speed_max_MEAN15
ANDVI
D_wind_speed_avg_MEAN15
solar_rad_max_MEAN15
BUI
solar_rad_max_MEAN7
D_precip
solar_rad_max
solar_rad_max_MEAN3
precip_effective_MEAN15
temp_avg_MEAN15
rel_humid_min_MEAN15
D_precip_effective
D_precip_effective_MEAN15
rel_humid_MEAN15
rel_humid_min
Variable
Marginal Posterior Probability
0.00 0.25 0.50 0.75 1.00
estimate
40
20
0
-20

Fig. 11.

Mixed Effects Models Summary Tables

OLS UNPOOLED PCA

```
> summary(ols.fitunpooled)

Call:
lm(formula = Percent ~ ., data = train)

Residuals:
     Min       1Q   Median       3Q      Max 
-121.794  -18.163   -0.151   15.125  276.866 

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)    
(Intercept)                90.34907    3.63349  24.866  < 2e-16 ***
Fuelceanothus, bigpod      -9.18191    5.35982  -1.713 0.086754 .  
Fuelceanothus, hoaryleaf  -6.89557    5.30562  -1.300 0.193771    
Fuelchamise                -6.94294    3.85653  -1.800 0.071871 .  
Fuelchamise, new growth   -4.24398    4.05418  -1.047 0.295234    
Fuelsage, black            53.23029    4.77895  11.138  < 2e-16 *** - 0.5 Page
Fuelsage, purple           15.82263    4.33419   3.651 0.000264 ***
Fuelsagebrush, black       30.60409    3.68342   8.309  < 2e-16 ***
Fuelsagebrush, california 29.75615    3.47004   8.575  < 2e-16 ***
PC1                        -2.40044    0.06202 -38.702  < 2e-16 ***
PC2                        -0.76413    0.15660  -4.879 1.10e-06 ***
PC3                         5.49748    0.18605  29.549  < 2e-16 ***
PC4                        -1.25194    0.19013  -6.585 5.01e-11 ***
PC5                         5.88623    0.27043  21.766  < 2e-16 ***
PC6                         5.36799    0.26270  20.434  < 2e-16 ***
PC7                         0.98124    0.25881   3.791 0.000152 ***
PC8                        -3.78810    0.31380 -12.072  < 2e-16 ***
PC9                         2.97335    0.32158   9.246  < 2e-16 ***
PC10                       -3.18813    0.35829  -8.898  < 2e-16 ***
PC11                       -0.49677    0.37653  -1.319 0.187117    
PC12                       -0.96281    0.37617  -2.559 0.010511 *  
PC13                       -1.51371    0.42186  -3.588 0.000336 ***
PC14                        3.98379    0.45779   8.702  < 2e-16 ***
PC15                        0.81722    0.45942   1.779 0.075332 .  
PC16                        2.74596    0.49746   5.520 3.56e-08 ***
PC17                        3.21767    0.54190   5.938 3.08e-09 ***
PC18                       -1.31759    0.56726  -2.323 0.020233 *  
PC19                       -0.36341    0.72537  -0.501 0.616395    
PC20                        2.76027    0.65619   4.206 2.64e-05 ***
PC21                       -3.56657    0.80386  -4.437 9.32e-06 ***
PC22                       -0.45398    1.06621  -0.426 0.670279    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 34.08 on 5165 degrees of freedom
Multiple R-squared:  0.5564, Adjusted R-squared:  0.5538
```

F-statistic: 215.9 on 30 and 5165 DF, p-value: < 2.2e-16

LMER VARYING INTERCEPT PCA

REML criterion at convergence: 51437.6

```
Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.5824 -0.5340 -0.0053  0.4436  8.1285

Random effects:
 Groups   Name        Variance Std.Dev.
 Fuel     (Intercept)  491.1   22.16
 Residual             1161.6   34.08
Number of obs: 5196, groups:  Fuel, 9

Fixed effects:
             Estimate Std. Error         df t value Pr(>|t|)
(Intercept)  101.72771    7.43495    8.05795  13.682 7.33e-07 ***
PC1           -2.40057    0.06202 5165.51703 -38.705  < 2e-16 ***
PC2           -0.77219    0.15650 5172.79201  -4.934 8.30e-07 ***
PC3            5.49892    0.18594 5172.39452  29.573  < 2e-16 ***
PC4           -1.25622    0.19008 5169.30756  -6.609 4.26e-11 ***
PC5            5.90222    0.26980 5143.02946  21.876  < 2e-16 ***
PC6            5.35703    0.26257 5172.05228  20.403  < 2e-16 ***
PC7            0.98146    0.25875 5168.63043   3.793 0.000151 ***
PC8           -3.78995    0.31375 5168.05752 -12.080  < 2e-16 ***
PC9            2.97518    0.32148 5170.13895   9.255  < 2e-16 ***
PC10          -3.18850    0.35781 5169.14229  -8.911  < 2e-16 ***
PC11          -0.49243    0.37648 5167.58463  -1.308 0.190934
PC12          -0.97027    0.37615 5166.38500  -2.580 0.009922 **
PC13          -1.49340    0.42133 5170.26282  -3.544 0.000397 ***
PC14           3.98472    0.45763 5170.56984   8.707  < 2e-16 ***
PC15           0.81916    0.45938 5166.70726   1.783 0.074618 .
PC16           2.75312    0.49695 5172.30417   5.540 3.17e-08 ***
PC17           3.21448    0.54171 5170.58996   5.934 3.15e-09 ***
PC18          -1.32361    0.56683 5172.98625  -2.335 0.019576 *
PC19          -0.38264    0.72045 4746.94509  -0.531 0.595359
PC20           2.77650    0.65506 5162.00397   4.239 2.29e-05 ***
PC21          -3.58744    0.79886 4819.42295  -4.491 7.27e-06 ***
PC22          -0.40905    1.05592 4314.79505  -0.387 0.698486
---
Signif. Codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

number of obs: 5196, groups: Fuel, 9
AIC = 51487.6, DIC = 51438
deviance = 51437.8
> fixef(lmer.fitfe)
(Intercept)         PC1         PC2         PC3         PC4         PC5         PC6         PC7         PC8
```

```
101.7277099  -2.4005709  -0.7721950   5.4989213  -1.2562240   5.9022160   5.3570319   0.9814564  -
3.7899516
       PC9       PC10       PC11       PC12       PC13       PC14       PC15       PC16       PC17
  2.9751806  -3.1884971  -0.4924312  -0.9702731  -1.4933964   3.9847200   0.8191558   2.7531216
3.2144839
      PC18       PC19       PC20       PC21       PC22
 -1.3236072  -0.3826443   2.7764967  -3.5874386  -0.4090528
> ranef(lmer.fitfe)
$Fuel
                          (Intercept)
buckwheat, eastern mojave  -11.306334
ceanothus, bigpod          -20.145550
ceanothus, hoaryleaf       -17.821270
chamise                    -18.274446
chamise, new growth        -15.568883
sage, black                 41.651880
sage, purple                 4.309138
sagebrush, black            18.982179
sagebrush, california       18.173285

with conditional variances for "Fuel"
```

PCA LMER VARYING SLOPE PC 22

```
 summary(lmer.fitre)
Linear mixed model fit by REML ['lmerMod']
Formula: Percent ~ +PC1 + PC2 + PC3 + PC4 + PC5 + PC6 + PC7 + PC8 + PC9 +
    PC10 + PC11 + PC12 + PC13 + PC14 + PC15 + PC16 + PC17 + PC18 +
    PC19 + PC20 + PC21 + PC22 + (1 + PC1 + PC2 + PC3 + PC4 +
    PC5 + PC6 + PC7 + PC8 + PC9 + PC10 + PC11 + PC12 + PC13 +
    PC14 + PC15 + PC16 + PC17 + PC18 + PC19 + PC20 + PC21 + PC22 |      Fuel)
   Data: train

REML criterion at convergence: 49584.1

Scaled residuals:
    Min      1Q  Median      3Q     Max
-5.8002 -0.4594 -0.0660  0.3866  7.5433

AIC = 50184.1, DIC = 49606.9
deviance = 49595.5

Random effects:
 Groups   Name        Variance Std.Dev. Corr
 Fuel     (Intercept) 803.681  28.349
          PC1           5.290   2.300   -0.89
          PC2           5.056   2.249   -0.91  0.70
          PC3          12.084   3.476    0.61 -0.67 -0.49
          PC4           3.501   1.871   -0.47  0.05  0.71 -0.09
          PC5          27.292   5.224    0.92 -0.66 -0.94  0.35 -0.68
          PC6          11.002   3.317    0.00 -0.41  0.20 -0.06  0.77 -0.20
          PC7           4.828   2.197   -0.10  0.07  0.11  0.64  0.02 -0.28 -0.37
          PC8          15.535   3.941   -0.43  0.66  0.17 -0.07 -0.44 -0.30 -0.80  0.59
          PC9          21.645   4.652   -0.32  0.13  0.45  0.52  0.42 -0.59 -0.07  0.88  0.35
          PC10         36.140   6.012   -0.08  0.32 -0.14 -0.78 -0.42  0.25 -0.13 -0.72  0.05 -0.87
          PC11         11.043   3.323    0.08  0.09 -0.16  0.53 -0.44  0.00 -0.69  0.86  0.76  0.59 -0.40
          PC12          1.002   1.001   -0.19  0.12  0.08 -0.76  0.08 -0.07  0.43 -0.76 -0.26 -0.67  0.75 -0.61
          PC13          3.381   1.839    0.34  0.07 -0.34  0.11 -0.71  0.51 -0.80  0.04  0.30 -0.17  0.14  0.36 -
0.44
          PC14         42.438   6.514    0.09 -0.06 -0.13 -0.66 -0.02  0.31  0.39 -0.96 -0.55 -0.91  0.80 -0.84
0.78
          PC15         20.543   4.532    0.53 -0.41 -0.57 -0.25 -0.31  0.72  0.23 -0.83 -0.60 -0.93  0.64 -0.66
0.48
          PC16         14.457   3.802   -0.32  0.40  0.22 -0.94 -0.01 -0.05  0.16 -0.85 -0.18 -0.77  0.88 -0.69
0.84
          PC17         33.695   5.805   -0.81  0.96  0.63 -0.47 -0.05 -0.61 -0.58  0.28  0.78  0.29  0.15  0.30 -
0.12
          PC18         19.807   4.450   -0.22  0.28  0.03 -0.66 -0.01  0.08  0.20 -0.61 -0.14 -0.70  0.78 -0.59
0.60
          PC19         53.654   7.325    0.77 -0.69 -0.70  0.95 -0.36  0.61 -0.23  0.51 -0.04  0.28 -0.57  0.52 -
0.72
```

```
        PC20        16.652   4.081   -0.77  0.80  0.65 -0.92  0.14 -0.58 -0.06 -0.40  0.29 -0.22  0.57 -0.30
0.62
        PC21        19.828   4.453    0.74 -0.56 -0.77  0.59 -0.48  0.79 -0.19  0.18 -0.10 -0.20 -0.05  0.24 -
0.42
        PC22       166.144  12.890   -0.77  0.84  0.67 -0.30  0.05 -0.71 -0.51  0.37  0.71  0.49 -0.12  0.36
-0.21
 Residual           795.169  28.199


 -0.10
  0.14  0.86
 -0.06  0.87  0.56
  0.23 -0.28 -0.54  0.18
 -0.21  0.78  0.61  0.74  0.09
  0.34 -0.51 -0.03 -0.82 -0.49 -0.54
 -0.11  0.36 -0.09  0.76  0.65  0.36 -0.94
  0.34 -0.03  0.40 -0.39 -0.46  0.11  0.76 -0.81
  0.17 -0.47 -0.71 -0.01  0.91 -0.26 -0.39  0.60 -0.64

Number of obs: 5196, groups:  Fuel, 9

Fixed effects:
             Estimate Std. Error t value
(Intercept) 102.159610   9.533473  10.716
PC1          -3.524480   0.771460  -4.569
PC2          -2.435503   0.778665  -3.128
PC3           5.467911   1.187196   4.606
PC4          -1.620722   0.655697  -2.472
PC5           6.745871   1.777455   3.795
PC6           7.472531   1.159830   6.443
PC7           0.009153   0.780184   0.012
PC8          -4.112841   1.359867  -3.024
PC9           0.748703   1.591438   0.470
PC10         -2.532473   2.061398  -1.229
PC11         -1.276728   1.179744  -1.082
PC12         -0.556315   0.477268  -1.166
PC13         -2.562233   0.745023  -3.439
PC14          4.479836   2.240995   1.999
PC15          2.638483   1.581669   1.668
PC16          1.045858   1.358025   0.770
PC17         -5.575626   2.013150  -2.770
PC18          1.293264   1.628246   0.794
PC19          3.116295   2.614244   1.192
PC20         -1.643172   1.511750  -1.087
PC21          1.548906   1.773224   0.873
PC22        -14.302977   4.520551  -3.164

Correlation matrix not shown by default, as p = 23 > 12.
Use print(x, correlation=TRUE)  or
```

```
  vcov(x)      if you need it

optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see ?isSingular

> ranef(lmer.fitre)
$Fuel
                           (Intercept)      PC1      PC2      PC3       PC4       PC5      PC6       PC7
buckwheat, eastern mojave  -24.297751  1.727436  1.518866 -2.789613 -0.02500918 -5.112870 -
0.5391004  0.05067324
ceanothus, bigpod         -21.269493  1.466454  1.336627 -1.449432  1.04585093 -2.699625  0.9485000
0.43425843
ceanothus, hoaryleaf      -24.374670  1.998247  1.349429 -2.148322  0.15262909 -3.690090 -
0.7721762  0.01206455
chamise                   -21.272192  2.272051  2.387785 -1.718009  0.39392993 -3.161203 -2.3017871
0.81833187
chamise, new growth       -19.055170  2.035972  0.463812 -1.123134 -0.47816148 -1.524552 -
1.9603212 -0.10965280
sage, black                4.387123 -2.922466  1.176893  2.369455  3.88842020 -3.268529  7.6573820 -
0.19103571
sage, purple              33.505812 -2.394656 -1.717689  5.632203 -0.84413728  4.014206 -2.0321112
1.63206380
sagebrush, black          33.549453 -1.830317 -2.712239 -3.684496 -1.58968830  8.753721  1.5103951
-5.15118654
sagebrush, california     38.826890 -2.352721 -3.803484  4.911349 -2.54383391  6.688941 -
2.5107811  2.50448315
                                PC8        PC9      PC10       PC11       PC12      PC13      PC14       PC15
buckwheat, eastern mojave  3.1793935   1.1353027  2.1092411  1.39758830  0.98622025 -0.8471196 -
1.4849153 -3.79908658
ceanothus, bigpod          0.8454297   0.3516918  1.5509705 -0.74295281  0.05591793 -1.0910067
1.2951639 -0.40066298
ceanothus, hoaryleaf       2.3230019   0.5395975  1.6241217  0.03366582  0.30040996 -0.3978924 -
0.3551190 -1.77805461
chamise                    2.2292502   2.3434940 -0.3020942  1.26129795 -0.53261780  1.6643995 -
2.0964469 -3.13134172
chamise, new growth        2.2275159  -0.2838822  1.1243180 -0.60234630 -0.30240327  0.3508165 -
0.2772512  0.05985803
sage, black               -7.1617556   3.2458703 -7.7438958 -3.59672756  0.18185283 -3.4012540
0.3277693 -0.51805511
sage, purple              -0.9909669   3.7159992 -8.6571682  2.55527932 -1.61388506  2.1364377 -
7.4093881 -1.49292501
sagebrush, black          -5.6013728 -11.5854538 11.4684918 -5.54349169  1.56461529  1.0157383
15.2959420 11.19994491
sagebrush, california      2.9495039   0.5373805 -1.1739850  5.23768698 -0.64011013  0.5698805 -
5.2957548 -0.13967694
                               PC16      PC17       PC18       PC19       PC20       PC21        PC22
buckwheat, eastern mojave  1.8147998  3.720446 -2.3066124 -7.3233727  5.4006825 -6.8225946
12.69652396
```

ceanothus, bigpod 0.9408457 2.922930 4.8464668 -3.5250374 0.6186963 1.2808803 -0.16322235
ceanothus, hoaryleaf 1.3921727 4.662440 0.9594377 -5.0574452 3.2649359 -3.1558689 10.32834066
chamise 0.6976611 6.370107 -1.0255806 -3.6596200 2.6009982 -1.8949345 12.06376312
chamise, new growth 0.6331296 5.342886 2.3242514 -1.7280432 1.4407763 -0.5283111 10.55204616
sage, black -2.0649229 -8.506102 -1.6382719 0.7860526 -3.0225630 -1.5211769 -13.33691016
sage, purple -5.5929488 -3.368748 -7.8782578 12.0089883 -5.3667284 2.5121333 0.07871954
sagebrush, black 6.8691443 -6.809591 6.2326127 -3.5117377 1.1731600 2.3131798 -19.85877892
sagebrush, california -4.6898814 -4.334366 -1.5140461 12.0102152 -6.1099579 7.8166926 -12.36048201

with conditional variances for “Fuel”

LMER VARYING SLOPE PCA6

REML criterion at convergence: 50087.4

Scaled residuals:

Min	1Q	Median	3Q	Max
-5.0543	-0.4548	-0.0698	0.3854	8.6589

Random effects:

Groups	Name	Variance	Std.Dev.	Corr					
Fuel	(Intercept)	384.623	19.6118						
	PC1	4.924	2.2189	-0.99					
	PC2	1.724	1.3131	-0.78	0.78				
	PC3	7.561	2.7497	0.95	-0.94	-0.66			
	PC4	0.510	0.7142	0.11	-0.03	0.46	0.30		
	PC5	4.271	2.0666	0.62	-0.69	-0.67	0.75	-0.11	
	PC6	6.881	2.6232	0.96	-0.92	-0.61	0.97	0.38	0.58
Residual		888.181	29.8024						

Number of obs: 5196, groups: Fuel, 9

```
Fixed effects:
            Estimate Std. Error        df t value Pr(>|t|)
(Intercept)  100.3245     6.5737    7.9018  15.261 3.82e-07 ***
PC1          -3.4269     0.7445    7.9703  -4.603 0.001766 **
PC2          -2.1448     0.4905    8.4286  -4.373 0.002094 **
PC3           6.2248     0.9446    7.5515   6.590 0.000221 ***
PC4          -1.8668     0.3155    5.1477  -5.916 0.001779 **
PC5           6.1051     0.7696    6.3411   7.933 0.000161 ***
PC6           7.0221     0.9169    7.7883   7.659 6.89e-05 ***
PC7           0.5697     0.2308 2646.8690   2.469 0.013629 *
PC8          -2.7014     0.2780 4250.1914  -9.718  < 2e-16 ***
PC9           2.3983     0.2816 4925.4098   8.517  < 2e-16 ***
PC10         -2.6686     0.3143 1239.8898  -8.490  < 2e-16 ***
PC11         -0.2875     0.3317 4879.6124  -0.867 0.386123
PC12         -1.1701     0.3297 4968.3587  -3.549 0.000391 ***
PC13         -1.0057     0.3717  760.9854  -2.706 0.006971 **
PC14          2.8880     0.4072 4026.3405   7.092 1.55e-12 ***
PC15          0.5728     0.4047 4981.5157   1.415 0.157077
PC16          1.7036     0.4401 2150.9418   3.871 0.000112 ***
PC17         -0.8750     0.4865 2911.3198  -1.798 0.072204 .
PC18         -0.5896     0.5009 2916.6217  -1.177 0.239225
PC19          0.4728     0.5941  393.6697   0.796 0.426582
PC20          0.9990     0.5655 3026.4145   1.767 0.077405 .
PC21         -2.0444     0.6664  286.7560  -3.068 0.002360 **
PC22         -2.6366     0.8656   85.1087  -3.046 0.003087 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
AIC = 50191.4, DIC = 50089.7
deviance = 50088.5
> fixef(lmer.fitre)
(Intercept)         PC1         PC2         PC3         PC4         PC5         PC6         PC7         PC8
100.3245324  -3.4268566  -2.1447532   6.2247819  -1.8668322   6.1050837   7.0220773   0.5697075  -2.7013872
```

PC9 PC10 PC11 PC12 PC13 PC14 PC15 PC16 PC17

2.3982616 -2.6686383 -0.2874630 -1.1700753 -1.0057298 2.8879500 0.5727556 1.7036431 -0.8750440

PC18 PC19 PC20 PC21 PC22

-0.5895972 0.4728448 0.9989910 -2.0444358 -2.6366280

> ranef(lmer.fitre)

$Fuel

	(Intercept)	PC1	PC2	PC3	PC4	PC5	PC6
buckwheat, eastern mojave	-7.57394	1.196576	0.16710661	-2.439758	-0.3747988	-3.0180870	-1.4508522
ceanothus, bigpod	-16.90292	1.839306	0.89111335	-1.123328	0.2637997	0.6075177	-1.6516621
ceanothus, hoaryleaf	-17.77743	1.901458	0.61246905	-2.619416	-0.3904516	-1.0463737	-2.6115127
chamise	-19.32866	2.175933	2.14496292	-2.483957	0.6190531	-2.4619768	-1.9420065
chamise, new growth	-15.15657	1.877486	0.30402548	-1.906482	-0.1773889	-0.6555276	-1.9225857
sage, black	33.63232	-3.343953	-1.02442977	4.732403	0.9201436	1.0209258	5.1183308
sage, purple	10.72493	-1.463315	0.02072088	2.155158	0.4249895	1.6396268	1.7330651
sagebrush, black	15.13650	-2.266287	-1.51057320	1.305353	-0.9796994	1.8674996	0.7626213
sagebrush, california	17.24577	-1.917204	-1.60539531	2.380027	-0.3056470	2.0463952	1.9646020

with conditional variances for “Fuel”

> summary(lmer.fitre)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: lmerRE_formula

Data: train

LMER VARYING SLOPE PCA MIN (1, 2, 3, 5, 6)

```
summary(lmer.fitre_2)
Linear mixed model fit by REML ['lmerMod']
Formula: lmerRE_formula2
   Data: train
Control: lmerControl(optCtrl = list(maxfun = 2e+05))

REML criterion at convergence: 50087.4

AIC = 50191.4, DIC = 50089.7
deviance = 50088.5
Scaled residuals:
    Min      1Q  Median      3Q     Max
-5.0543 -0.4548 -0.0698  0.3854  8.6589

Random effects:
 Groups   Name        Variance Std.Dev. Corr
 Fuel     (Intercept) 384.623  19.6118
          PC1           4.924   2.2189  -0.99
          PC2           1.724   1.3131  -0.78  0.78
          PC3           7.561   2.7497   0.95 -0.94 -0.66
          PC4           0.510   0.7142   0.11 -0.03  0.46  0.30
          PC5           4.271   2.0666   0.62 -0.69 -0.67  0.75 -0.11
          PC6           6.881   2.6232   0.96 -0.92 -0.61  0.97  0.38  0.58
 Residual             888.181  29.8024
Number of obs: 5196, groups:  Fuel, 9

Fixed effects:
            Estimate Std. Error t value
(Intercept) 100.3245     6.5737  15.261
```

```
PC1      -3.4269   0.7445  -4.603
PC2      -2.1448   0.4905  -4.373
PC3       6.2248   0.9446   6.590
PC4      -1.8668   0.3155  -5.916
PC5       6.1051   0.7696   7.933
PC6       7.0221   0.9169   7.659
PC7       0.5697   0.2308   2.469
PC8      -2.7014   0.2780  -9.718
PC9       2.3983   0.2816   8.517
PC10     -2.6686   0.3143  -8.490
PC11     -0.2875   0.3317  -0.867
PC12     -1.1701   0.3297  -3.549
PC13     -1.0057   0.3717  -2.706
PC14      2.8880   0.4072   7.092
PC15      0.5728   0.4047   1.415
PC16      1.7036   0.4401   3.871
PC17     -0.8750   0.4865  -1.798
PC18     -0.5896   0.5009  -1.177
PC19      0.4728   0.5941   0.796
PC20      0.9990   0.5655   1.767
PC21     -2.0444   0.6664  -3.068
PC22     -2.6366   0.8656  -3.046

Correlation matrix not shown by default, as p = 23 > 12.
Use print(x, correlation=TRUE)  or
    vcov(x)        if you need it

optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see ?isSingular

> fixef(lmer.fitre_2)
(Intercept)        PC1        PC2        PC3        PC4        PC5        PC6        PC7        PC8
```

100.3245324 -3.4268566 -2.1447532   6.2247819 -1.8668322   6.1050837   7.0220773   0.5697075 -2.7013872

PC9   PC10   PC11   PC12   PC13   PC14   PC15   PC16   PC17

2.3982616 -2.6686383 -0.2874630 -1.1700753 -1.0057298   2.8879500   0.5727556   1.7036431 -0.8750440

PC18   PC19   PC20   PC21   PC22

-0.5895972   0.4728448   0.9989910 -2.0444358 -2.6366280

> ranef(lmer.fitre_2)

$Fuel

(Intercept)   PC1   PC2   PC3   PC4   PC5   PC6

buckwheat, eastern mojave   -7.57394 1.196576 0.16710661 -2.439758 -0.3747988 -3.0180870 -1.4508522

ceanothus, bigpod   -16.90292 1.839306 0.89111335 -1.123328 0.2637997 0.6075177 -1.6516621

ceanothus, hoaryleaf   -17.77743 1.901458 0.61246905 -2.619416 -0.3904516 -1.0463737 -2.6115127

chamise   -19.32866 2.175933 2.14496292 -2.483957 0.6190531 -2.4619768 -1.9420065

chamise, new growth   -15.15657 1.877486 0.30402548 -1.906482 -0.1773889 -0.6555276 -1.9225857

sage, black   33.63232 -3.343953 -1.02442977 4.732403 0.9201436 1.0209258 5.1183308

sage, purple   10.72493 -1.463315 0.02072088 2.155158 0.4249895 1.6396268 1.7330651

sagebrush, black   15.13650 -2.266287 -1.51057320 1.305353 -0.9796994 1.8674996 0.7626213

sagebrush, california   17.24577 -1.917204 -1.60539531 2.380027 -0.3056470 2.0463952 1.9646020

with conditional variances for “Fuel”

OLS UNPOOLED BMS RESULTS

```
 summary(ols.fitunpooled)

Call:
lm(formula = OLS_formula, data = train)

Residuals:
     Min       1Q   Median       3Q      Max 
-139.863  -17.471   -0.931   13.781  277.208 

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)    
(Intercept)              95.3045     0.4634 205.672  < 2e-16 ***
solar_rad_avg_MEAN7       4.2262     3.2279   1.309 0.190502    
D_solar_rad_max          -3.0330     6.4000  -0.474 0.635580    
D_solar_rad_avg          19.0510     5.3898   3.535 0.000412 ***
rel_humid_MEAN15         -6.3504     3.1180  -2.037 0.041734 *  
rel_humid_min_MEAN15     13.8779     3.7014   3.749 0.000179 ***
solar_rad_max_MEAN7      -2.0454     3.6334  -0.563 0.573491    
D_rel_humid_min_MEAN15   13.6653     7.8076   1.750 0.080135 .  
BUI                      -0.5406     6.3609  -0.085 0.932277    
DMC                       2.5545     5.6027   0.456 0.648447    
evap_pot_MEAN7           -0.6782     5.6472  -0.120 0.904415    
evap_pot_MEAN15          17.1050     5.3575   3.193 0.001418 ** 
D_solar_rad_avg_MEAN7     1.0319     5.9296   0.174 0.861848    
temp_avg_MEAN15           3.5973     8.3744   0.430 0.667536    
rel_humid_min             5.8641     1.2219   4.799 1.64e-06 ***
D_temp_avg              -36.1313     8.7087  -4.149 3.40e-05 ***
D_temp_min               27.1989     5.4460   4.994 6.10e-07 ***
solar_rad_avg             5.9643     1.8361   3.248 0.001168 ** 
rel_humid_min_MEAN7      -0.5118     2.9841  -0.171 0.863840    
```

ANDVI	-27.4837	1.6595	-16.561	< 2e-16	***
D_solar_rad_max_MEAN7	9.4870	15.2081	0.624	0.532779	
D_evap_pot_MEAN15	-15.4856	3.7413	-4.139	3.54e-05	***
plant_height_ANDVI	-5.0483	0.8144	-6.199	6.13e-10	***
D_BUI	21.7762	8.3966	2.593	0.009529	**
solar_rad_max_MEAN15	7.8009	3.7294	2.092	0.036513	*
D_solar_rad_max_MEAN15	7.5000	12.9145	0.581	0.561443	
D_rel_humid_MEAN15	0.2474	8.9323	0.028	0.977902	
SLA_ANDVI	-11.3386	1.3405	-8.458	< 2e-16	***
temp_max_MEAN15	-2.6472	5.1362	-0.515	0.606300	
solar_rad_avg_MEAN15	-0.5816	3.5246	-0.165	0.868952	
D_rel_humid_min_MEAN7	2.3497	4.0055	0.587	0.557486	
D_DC	-8.9809	2.0371	-4.409	1.06e-05	***
D_temp_avg_MEAN3	-0.3008	10.1998	-0.029	0.976471	
D_temp_max_MEAN3	10.4076	11.8252	0.880	0.378836	
D	20.0892	8.4668	2.373	0.017695	*
D_solar_rad_max_MEAN3	6.8056	8.0365	0.847	0.397125	
D_temp_avg_MEAN15	190.8168	33.9838	5.615	2.07e-08	***
D_wind_speed_max_MEAN7	-11.2647	3.6054	-3.124	0.001792	**
D_wind_speed_avg_MEAN15	6.2173	3.9978	1.555	0.119962	
leaf_phos_ANDVI	37.4553	1.7508	21.394	< 2e-16	***
station_elevation	-2.8973	0.6341	-4.569	5.02e-06	***
D_temp_max_MEAN15	-142.0548	26.1811	-5.426	6.03e-08	***
D_temp_min_MEAN15	-56.9366	13.6568	-4.169	3.11e-05	***
evap_pot_MEAN3	2.4980	3.3386	0.748	0.454355	
rel_humid	-0.7232	1.0716	-0.675	0.499788	
rel_humid_MEAN7	-0.5614	2.5679	-0.219	0.826963	
solar_rad_max_MEAN3	0.9256	1.5605	0.593	0.553139	
DC	-8.4607	1.3264	-6.379	1.94e-10	***
temp_min_MEAN15	-9.7464	4.1361	-2.356	0.018489	*
wind_speed_avg_MEAN15	0.8418	0.5710	1.474	0.140492	
D_DMC	-17.5052	7.1634	-2.444	0.014571	*

```
leaf_nitr_mass_ANDVI      15.9573     1.1820  13.500  < 2e-16 ***
D_wind_speed_max          -4.1069     1.8520  -2.218 0.026632 *
solar_rad_max              0.2939     1.5876   0.185 0.853121
D_rel_humid_min            0.8618     2.2425   0.384 0.700778
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 33.4 on 5141 degrees of freedom
Multiple R-squared:  0.5759, Adjusted R-squared:  0.5714
F-statistic: 129.3 on 54 and 5141 DF,  p-value: < 2.2e-16
LMER VARYING INTERCEPT BMS RESULTS
REML criterion at convergence: 50702.2
Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.0986 -0.5473 -0.0055  0.4469  8.6123

Random effects:
 Groups   Name        Variance Std.Dev.
 Fuel     (Intercept)  331     18.19
 Residual             1053     32.45
Number of obs: 5196, groups:  Fuel, 9

Fixed effects:
                         Estimate Std. Error        df t value Pr(>|t|)
(Intercept)              98.0137     6.2097    7.7946  15.784 3.40e-07 ***
solar_rad_avg_MEAN7       3.6462     3.1366 5133.5280   1.162 0.245112
D_solar_rad_max          -1.5578     6.2225 5133.4014  -0.250 0.802325
D_solar_rad_avg          17.4082     5.2381 5133.4064   3.323 0.000896 ***
rel_humid_MEAN15         -4.9322     3.0304 5133.1795  -1.628 0.103672
rel_humid_min_MEAN15     11.9166     3.6025 5134.0601   3.308 0.000947 ***
solar_rad_max_MEAN7      -2.1559     3.5307 5133.5325  -0.611 0.541488
D_rel_humid_min_MEAN15   13.9707     7.5896 5134.0955   1.841 0.065711 .
```

BUI	-1.3562	6.1997	5135.6488	-0.219	0.826854	
DMC	3.1304	5.4591	5134.8638	0.573	0.566382	
evap_pot_MEAN7	0.4764	5.4881	5133.2869	0.087	0.930829	
evap_pot_MEAN15	16.2339	5.2075	5133.9379	3.117	0.001834	**
D_solar_rad_avg_MEAN7	1.4802	5.7644	5133.5207	0.257	0.797358	
temp_avg_MEAN15	0.1798	8.2228	5139.3275	0.022	0.982554	
rel_humid_min	5.5640	1.1880	5133.9269	4.683	2.89e-06	***
D_temp_avg	-34.5467	8.4618	5133.2827	-4.083	4.52e-05	***
D_temp_min	26.4054	5.2918	5133.0913	4.990	6.24e-07	***
solar_rad_avg	5.8085	1.7843	5133.4238	3.255	0.001140	**
rel_humid_min_MEAN7	0.2666	2.9001	5133.4739	0.092	0.926770	
ANDVI	3.1833	3.3722	754.6908	0.944	0.345469	
D_solar_rad_max_MEAN7	8.4770	14.7767	5133.3778	0.574	0.566215	
D_evap_pot_MEAN15	-14.7997	3.6362	5133.2274	-4.070	4.77e-05	***
plant_height_ANDVI	-14.0656	1.6896	2301.8675	-8.325	< 2e-16	***
D_BUI	23.3338	8.1722	5133.9070	2.855	0.004317	**
solar_rad_max_MEAN15	6.2365	3.6309	5134.5998	1.718	0.085930	.
D_solar_rad_max_MEAN15	4.4939	12.5529	5133.5526	0.358	0.720362	
D_rel_humid_MEAN15	-0.6256	8.6936	5134.3251	-0.072	0.942633	
SLA_ANDVI	-12.3092	2.9629	589.0492	-4.154	3.74e-05	***
temp_max_MEAN15	0.7779	5.0375	5138.5762	0.154	0.877276	
solar_rad_avg_MEAN15	1.0026	3.4282	5134.0685	0.292	0.769957	
D_rel_humid_min_MEAN7	2.1347	3.8919	5133.4340	0.548	0.583373	
D_DC	-9.4306	1.9826	5133.8185	-4.757	2.02e-06	***
D_temp_avg_MEAN3	-0.4571	9.9124	5133.6803	-0.046	0.963218	
D_temp_max_MEAN3	10.0990	11.4917	5133.5196	0.879	0.379548	
D	20.5273	8.2293	5133.3748	2.494	0.012647	*
D_solar_rad_max_MEAN3	10.1933	7.8116	5133.5488	1.305	0.191988	
D_temp_avg_MEAN15	193.4086	33.0733	5134.6047	5.848	5.29e-09	***
D_wind_speed_max_MEAN7	-12.2245	3.5098	5135.3925	-3.483	0.000500	***
D_wind_speed_avg_MEAN15	5.6005	3.8868	5133.6691	1.441	0.149675	
leaf_phos_ANDVI	21.6337	3.8310	854.0039	5.647	2.22e-08	***

station_elevation	-1.6750	0.6524	5132.6196	-2.568	0.010270	*
D_temp_max_MEAN15	-140.7457	25.4635	5133.8897	-5.527	3.41e-08	***
D_temp_min_MEAN15	-60.6595	13.2949	5135.2222	-4.563	5.17e-06	***
evap_pot_MEAN3	1.9396	3.2454	5133.6649	0.598	0.550092	
rel_humid	-0.7140	1.0416	5133.7311	-0.686	0.493045	
rel_humid_MEAN7	-1.0495	2.4960	5134.1770	-0.420	0.674169	
solar_rad_max_MEAN3	1.4019	1.5172	5133.7454	0.924	0.355526	
DC	-8.0820	1.2956	5137.4380	-6.238	4.78e-10	***
temp_min_MEAN15	-9.0259	4.0457	5138.1550	-2.231	0.025725	*
wind_speed_avg_MEAN15	1.6727	0.5697	5140.9983	2.936	0.003340	**
D_DMC	-18.7817	6.9687	5133.7357	-2.695	0.007059	**
leaf_nitr_mass_ANDVI	5.5554	2.6180	1205.3154	2.122	0.034039	*
D_wind_speed_max	-3.7978	1.7995	5133.3520	-2.110	0.034871	*
solar_rad_max	0.4242	1.5433	5134.0375	0.275	0.783421	
D_rel_humid_min	1.3730	2.1786	5132.9666	0.630	0.528583	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

AIC = 50816.2, DIC = 51080.8

deviance = 50891.5

LMER VARYING SLOPE BMS (11)

```
summary(lmer.fitre)
Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: lmerRE_formula
   Data: train
Control: lmerControl(optCtrl = list(maxfun = 2e+05))

REML criterion at convergence: 49485.5

Scaled residuals:
    Min      1Q  Median      3Q     Max
-5.5661 -0.4579 -0.0610  0.3875  8.3650

Random effects:
 Groups   Name                  Variance Std.Dev. Corr
 Fuel     (Intercept)          684.412  26.161
          rel_humid              4.200   2.049    0.86
          rel_humid_MEAN7       26.803   5.177    0.51  0.61
          solar_rad_max_MEAN3    5.505   2.346    0.47  0.37  0.78
          DC                   190.562  13.804   -0.81 -0.46 -0.02 -0.07
          temp_min_MEAN15      128.428  11.333   -0.61 -0.47  0.24  0.15  0.76
          wind_speed_avg_MEAN15  37.582   6.130    0.71  0.76  0.87  0.86 -0.21 -0.08
          D_DMC                 66.906   8.180   -0.78 -0.46 -0.15 -0.12  0.93  0.71 -0.29
          leaf_nitr_mass_ANDVI  12.220   3.496    0.69  0.40  0.13  0.34 -0.75 -0.60  0.29 -0.54
          D_wind_speed_max     248.525  15.765    0.83  0.80  0.86  0.73 -0.43 -0.09  0.91 -0.48  0.38
          solar_rad_max          8.700   2.950    0.07  0.50  0.47  0.37  0.47  0.09  0.56  0.42 -0.18  0.27
          D_rel_humid_min       22.141   4.705    0.92  0.66  0.49  0.63 -0.77 -0.43  0.70 -0.69  0.76  0.82
 Residual                      809.849  28.458

 -0.08

Number of obs: 5196, groups:  Fuel, 9
```

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)	
(Intercept)	83.74688	2.18621	16.08718	38.307	< 2e-16	***
solar_rad_avg_MEAN7	4.34329	2.74224	5030.89586	1.584	0.113291	
D_solar_rad_max	-5.58160	5.37234	4448.20692	-1.039	0.298883	
D_solar_rad_avg	17.38704	4.24443	1774.92461	4.096	4.38e-05	***
rel_humid_MEAN15	-4.89468	1.93899	243.60789	-2.524	0.012228	*
rel_humid_min_MEAN15	11.92811	2.61773	868.61140	4.557	5.94e-06	***
solar_rad_max_MEAN7	0.04146	2.86785	1721.76135	0.014	0.988466	
D_rel_humid_min_MEAN15	6.16185	6.61898	4559.86011	0.931	0.351936	
BUI	-4.37142	5.09358	1093.29014	-0.858	0.390958	
DMC	3.44177	4.46373	1356.60638	0.771	0.440810	
evap_pot_MEAN7	-4.26094	4.63801	4098.42911	-0.919	0.358306	
evap_pot_MEAN15	17.40169	4.43026	4163.30652	3.928	8.71e-05	***
D_solar_rad_avg_MEAN7	7.24243	5.05995	5030.05194	1.431	0.152400	
temp_avg_MEAN15	-5.08051	4.55836	43.39085	-1.115	0.271180	
rel_humid_min	4.57181	0.74651	53.73941	6.124	1.10e-07	***
D_temp_avg	-31.89445	5.86524	295.11796	-5.438	1.13e-07	***
D_temp_min	21.07608	4.00256	784.09981	5.266	1.81e-07	***
solar_rad_avg	5.85494	1.03461	46.98452	5.659	8.81e-07	***
rel_humid_min_MEAN7	-0.62512	1.49668	73.33745	-0.418	0.677406	
ANDVI	-1.38685	2.77162	18.95349	-0.500	0.622570	
D_solar_rad_max_MEAN7	2.90877	12.93349	5067.06615	0.225	0.822064	
D_evap_pot_MEAN15	-13.30059	3.20561	4563.56263	-4.149	3.40e-05	***
plant_height_ANDVI	1.77236	1.55899	13.53430	1.137	0.275325	
D_BUI	7.29995	1.84944	14.31265	3.947	0.001403	**
solar_rad_max_MEAN15	5.10562	3.16414	5066.84538	1.614	0.106679	
D_solar_rad_max_MEAN15	4.46125	11.01837	5048.53787	0.405	0.685574	
D_rel_humid_MEAN15	5.35418	7.70165	4622.53402	0.695	0.486965	
SLA_ANDVI	2.55999	2.22219	23.24708	1.152	0.261027	
temp_max_MEAN15	5.33003	3.42268	224.17912	1.557	0.120817	

```
solar_rad_avg_MEAN15       1.37383    2.98918 5031.06656   0.460 0.645823
D_rel_humid_min_MEAN7      3.30716    3.32198 4348.04512   0.996 0.319530
D_DC                      -6.17769    1.28884 1900.05413  -4.793 1.77e-06 ***
D_temp_avg_MEAN3          -5.60532    8.68252 5027.68632  -0.646 0.518576
D_temp_max_MEAN3          18.86343   10.07509 5063.78053   1.872 0.061225 .
D                         -2.14995    7.21578 4815.61852  -0.298 0.765753
D_solar_rad_max_MEAN3      8.51670    6.75907 4427.31448   1.260 0.207721
D_temp_avg_MEAN15        102.88780   28.90902 2966.20238   3.559 0.000378 ***
D_wind_speed_max_MEAN7    -0.09593    3.05257 2329.83054  -0.031 0.974933
D_wind_speed_avg_MEAN15    3.05848    3.46474 3594.57047   0.883 0.377433
leaf_phos_ANDVI            0.55458    2.96222   11.69014   0.187 0.854699
station_elevation          1.05954    0.56872 1989.85870   1.863 0.062603 .
D_temp_max_MEAN15        -67.30265   22.58625 4270.87027  -2.980 0.002901 **
D_temp_min_MEAN15        -31.99910   11.42539 2204.30257  -2.801 0.005144 **
evap_pot_MEAN3             3.66928    2.80018 4989.52539   1.310 0.190130
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

AIC = 49731.5, DIC = 49783.2
deviance = 49634.3

> ranef(lmer.fitre)
$Fuel
                          (Intercept)  rel_humid rel_humid_MEAN7 solar_rad_max_MEAN3          DC
temp_min_MEAN15
buckwheat, eastern mojave   6.7261473  1.7145450      -2.4408797          -1.7791494  -0.6719208      -
10.287610
ceanothus, bigpod           1.7997868 -1.0391701      -0.8220261           1.3394980  -5.6272596      -
3.799655
ceanothus, hoaryleaf       -0.2078868 -0.1265346      -1.0271956          -0.3748715  -2.2477359      -
5.377938
chamise                    -3.2823566 -0.7493323      -1.4280700           0.4739268  -1.3014126      -
4.275382
```

chamise, new growth	1.8770095	-0.1501009	-0.8745918	-0.4067969	-4.9673267	-9.054864
sage, black	51.5038439	4.1614500	11.5097790	3.0995961	-14.9869543	-5.338318
sage, purple	32.5486343	2.0876896	6.8918780	4.5258451	-6.1274732	2.244661
sagebrush, black	33.4432766	0.3665556	-5.0764377	-1.9915710	-33.7016690	-17.582630
sagebrush, california	34.9206881	2.8413868	-0.3839877	0.9245203	-14.6527607	-21.359521

	wind_speed_avg_MEAN15	D_DMC	leaf_nitr_mass_ANDVI	D_wind_speed_max	solar_rad_max
buckwheat, eastern mojave	-0.03245517	-0.2062364	-1.000161	-2.577181	2.4199762
ceanothus, bigpod	0.18499790	-3.4767707	2.236573	-2.455728	-1.4529464
ceanothus, hoaryleaf	-1.17378353	-1.7661062	0.847302	-4.652696	-0.0202259
chamise	0.78226566	-4.8128393	-2.213953	-3.402674	-0.5121576
chamise, new growth	-1.98557913	-2.9569936	2.722868	-6.889021	-0.1310495
sage, black	12.43572111	-12.8612219	1.758236	36.304062	1.8779433
sage, purple	10.69315521	-1.1965424	3.928678	25.960543	1.8463639
sagebrush, black	-4.20750709	-17.2787102	5.130923	3.328361	-6.7640161
sagebrush, california	5.09696227	-6.4436372	4.917235	7.659588	2.6207663

	D_rel_humid_min
buckwheat, eastern mojave	-1.1716722
ceanothus, bigpod	1.7117295
ceanothus, hoaryleaf	-0.6883150
chamise	-0.6245079
chamise, new growth	-0.7004573
sage, black	7.2579869
sage, purple	8.1229903
sagebrush, black	6.3918234
sagebrush, california	4.9550212

with conditional variances for “Fuel”

LMER VARYING SLOPE BMS 6

REML criterion at convergence: 49530.4

```
Scaled residuals:
    Min      1Q  Median      3Q     Max
-5.3675 -0.4562 -0.0569  0.3822  8.8893

Random effects:
 Groups   Name                  Variance Std.Dev. Corr
 Fuel     (Intercept)          591.08   24.312
          rel_humid_MEAN7       32.93    5.738    0.59
          DC                   173.25   13.162   -0.83 -0.07
          temp_min_MEAN15      148.94   12.204   -0.63  0.11  0.80
          wind_speed_avg_MEAN15  43.29    6.579    0.71  0.89 -0.20 -0.13
          D_DMC                 52.36    7.236   -0.82 -0.26  0.90  0.68 -0.35
          D_wind_speed_max     330.14   18.170    0.90  0.76 -0.62 -0.23  0.79 -0.67
 Residual                      821.77   28.667
Number of obs: 5196, groups:  Fuel, 9

Fixed effects:
                       Estimate Std. Error         df t value Pr(>|t|)
(Intercept)            84.36273    1.77733   29.82691  47.466  < 2e-16 ***
solar_rad_avg_MEAN7     4.62714    2.77041 5107.54458   1.670 0.094941 .
D_solar_rad_max        -5.77600    5.49917 5110.98139  -1.050 0.293612
D_solar_rad_avg        17.06267    4.63489 5108.75169   3.681 0.000234 ***
rel_humid_MEAN15       -4.57441    1.99013  309.08549  -2.299 0.022198 *
rel_humid_min_MEAN15   11.45220    2.66527 1043.35857   4.297 1.89e-05 ***
rel_humid               0.04008    0.91752 5091.98382   0.044 0.965157
solar_rad_max_MEAN7    -1.79795    3.11127 5108.54842  -0.578 0.563368
D_rel_humid_min_MEAN15  6.37003    6.71970 5066.63799   0.948 0.343193
BUI                    -4.89836    5.00376  658.51260  -0.979 0.327971
DMC                     4.14026    4.41212  917.66054   0.938 0.348295
```

evap_pot_MEAN7	-4.32481	4.71988	4693.04137	-0.916	0.359558	
evap_pot_MEAN15	18.16085	4.46561	4830.37160	4.067	4.84e-05	***
D_solar_rad_avg_MEAN7	7.38467	5.13103	5097.23602	1.439	0.150150	
solar_rad_max_MEAN3	2.13100	1.34237	5116.63021	1.587	0.112463	
temp_avg_MEAN15	-3.60961	4.46200	65.35628	-0.809	0.421470	
rel_humid_min	5.20521	1.04692	5113.67632	4.972	6.85e-07	***
D_temp_avg	-30.59687	7.45555	5073.66225	-4.104	4.13e-05	***
D_temp_min	19.77145	4.65716	4932.36896	4.245	2.22e-05	***
solar_rad_avg	5.73616	1.57339	5107.28522	3.646	0.000269	***
rel_humid_min_MEAN7	-0.94283	1.55944	99.76376	-0.605	0.546820	
ANDVI	-2.07973	2.10328	161.20403	-0.989	0.324240	
D_solar_rad_max_MEAN7	2.23227	13.09435	5115.86175	0.170	0.864643	
D_evap_pot_MEAN15	-13.10796	3.23663	5084.92056	-4.050	5.20e-05	***
plant_height_ANDVI	-2.52110	1.13828	110.20393	-2.215	0.028829	*
leaf_nitr_mass_ANDVI	3.25968	1.72211	116.79245	1.893	0.060853	.
D_BUI	7.03335	1.89750	12.98707	3.707	0.002641	**
solar_rad_max_MEAN15	4.92480	3.19384	5103.31940	1.542	0.123144	
D_solar_rad_max_MEAN15	4.44663	11.13494	5099.02668	0.399	0.689659	
D_rel_humid_MEAN15	4.14609	7.74493	5018.10596	0.535	0.592446	
solar_rad_max	0.11393	1.36241	5119.30816	0.084	0.933361	
SLA_ANDVI	-1.74040	1.75931	99.82586	-0.989	0.324933	
temp_max_MEAN15	4.37792	3.37721	378.17044	1.296	0.195658	
solar_rad_avg_MEAN15	1.15530	3.01502	5087.40518	0.383	0.701601	
D_rel_humid_min_MEAN7	2.89186	3.43863	5071.95481	0.841	0.400391	
D_DC	-6.24436	1.30985	1813.69105	-4.767	2.02e-06	***
D_temp_avg_MEAN3	-4.98207	8.77522	5113.71966	-0.568	0.570234	
D_temp_max_MEAN3	17.60366	10.17518	5105.85688	1.730	0.083680	.
D	-4.21142	7.34522	5046.60140	-0.573	0.566430	
D_solar_rad_max_MEAN3	11.43488	6.91378	5114.70017	1.654	0.098204	.
D_temp_avg_MEAN15	104.51949	29.24242	4628.77461	3.574	0.000355	***
D_rel_humid_min	2.10399	1.91030	4943.19072	1.101	0.270779	
D_wind_speed_max_MEAN7	0.40640	3.09750	3705.67726	0.131	0.895623	

D_wind_speed_avg_MEAN15   3.69832   3.47364 4873.81904   1.065 0.287073

leaf_phos_ANDVI   7.63063   2.61119 130.28268   2.922 0.004098 **

station_elevation   0.96789   0.56507 2610.42433   1.713 0.086853 .

D_temp_max_MEAN15   -69.13857   22.68884 4861.51580 -3.047 0.002322 **

D_temp_min_MEAN15   -31.99502   11.70570 4627.84736 -2.733 0.006294 **

evap_pot_MEAN3   3.61630   2.86436 5111.17476   1.263 0.206822

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

AIC = 49686.4, DIC = 49850

deviance = 49690.2

> ranef(lmer.fitre_2)

$Fuel

(Intercept) rel_humid_MEAN7 DC temp_min_MEAN15
wind_speed_avg_MEAN15 D_DMC

buckwheat, eastern mojave 5.0154598 -0.8557605 -1.6273446 -10.4867224 1.6107756
0.3459325

ceanothus, bigpod 3.9529400 -2.0066080 -6.0819243 -6.1449116 -1.3049379 -
4.3568616

ceanothus, hoaryleaf -0.9963828 -0.8217512 0.2701879 -6.0944915 -0.4065867
0.5374437

chamise -0.4805027 -1.8252455 -1.2699540 -5.1260181 0.6352754 -
4.4191746

chamise, new growth 3.2253224 -0.5356192 -5.1519502 -10.4298073 -2.4071578 -
3.3300551

sage, black 50.4236409 13.0475093 -15.8383203 -5.9828659 13.5418014 -
12.8619097

sage, purple 29.6096980 7.4593216 -5.3701771 -0.2010607 10.5963291 -
1.7459492

sagebrush, black 29.1606872 -5.6518523 -30.5525479 -18.6287288 -5.1684990 -
12.7354356

sagebrush, california 30.5141862 0.5660951 -15.4114145 -22.9463928 5.2875583 -
6.2819572

D_wind_speed_max

buckwheat, eastern mojave -4.6867275

ceanothus, bigpod -0.7362326

ceanothus, hoaryleaf	-6.7247405
chamise	-4.0151397
chamise, new growth	-6.8115468
sage, black	41.0773081
sage, purple	27.2993192
sagebrush, black	14.6562206
sagebrush, california	9.1269121

with conditional variances for “Fuel”

References

Castro, F., Tudela, A., and Sebastià, M. T. (2003). Modeling moisture content in shrubs to predict fire risk in catalonia (spain). *Agricultural and Forest Meteorology*, 116(1-2):49–59.

Chuvieco, E., Cocero, D., Riano, D., Martin, P., Martınez-Vega, J., De La Riva, J., and Pérez, F. (2004). Combining ndvi and surface temperature for the estimation of live fuel moisture content in forest fire danger rating. *Remote Sensing of Environment*, 92(3):322–331.

Dennison, P. E. and Moritz, M. A. (2009). Critical live fuel moisture in chaparral ecosystems: a threshold for fire activity and its relationship to antecedent precipitation. *International Journal of Wildland Fire*, 18(8):1021–1027.

McCandless, T. C., Kosovic, B., and Petzke, W. (2020). Enhancing wildfire spread modelling by building a gridded fuel moisture content product with machine learning. *Machine Learning: Science and Technology*, 1(3):035010.

Ruffault, J., Martin-StPaul, N., Pimont, F., and Dupuy, J.-L. (2018). How well do meteorological drought indices predict live fuel moisture content (lfmc)? an assessment for wildfire research and operations in mediterranean ecosystems. *Agricultural and Forest Meteorology*, 262:391–401.

Westreich, D. and Greenland, S. (2013). The table 2 fallacy: presenting and interpreting confounder and modifier coefficients. *American journal of epidemiology*, 177(4):292–298.