Final Report for 15-AQP007

Incorporating Disturbance Effects on Fuels into the Emissions Estimation System

Prepared for

The California Air Resources Board and the California Environmental Protection Agency

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Disclaimer

The statements and conclusions in this Report are those of the contractor and not necessarily those of the California Air Resources Board. The mention of commercial products, their source, or their use in connection with material reported herein is not to be construed as actual or implied endorsement of such products.

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Abstract

The California Air Resources Board (CARB) uses Fuel Characteristic Classification System (FCCS) maps produced by the LANDFIRE program to estimate wildfire emissions. We developed and implemented a protocol for generating annual updates to the FCCS maps. The annual updates incorporate the effects of wildfire, timber harvest, and fuel treatments on wildland fuels. Three mapping strategies are compared: the status-quo system relying on a single legacy FCCS raster, an infrequent-update system relying on official LANDFIRE remaps, and a strategy using our annually-updated maps. Both the infrequently-updated and the annually-updated maps effectively capture the influence of disturbances on wildland fuels, producing more accurate inputs for emissions modeling software. We also present two methods for calibrating the fuel component loading estimates provided by the FCCS system based on empirical plot data. Both calibration methods indicate that the status quo Emissions Estimation System used by CARB may be substantially over-estimating surface fuel loads.

Executive Summary

Background

The California Air Resources Board (CARB) uses Fuel Characteristic Classification System (FCCS) maps produced by the LANDFIRE program to estimate wildfire emissions. The LANDFIRE team releases periodic updates to these maps, which reflect the influence of recent disturbances (e.g. wildfires, timber harvests, and fuel treatments) on wildland fuels. However, there is a substantial time lag (often several years) between when disturbances actually happen and when they are incorporated into an updated LANDFIRE map. This lag introduces a potential source of bias into CARB's wildfire emissions estimates, as wildfire emissions are estimated using out-of-date fuel maps. To address this issue, CARB and researchers at the University of California, Berkeley (UCB) partnered to develop and implement a method for updating the FCCS maps on-demand to depict wildland fuel changes caused by disturbances such as wildfire, timber harvest, and fuel treatments.

Methods

Source data for this project included the official LANDFIRE FCCS rasters depicting fuels throughout California at a 30-meter resolution for the years 2001, 2008, and 2014. Disturbance shapefiles provided information about wildfires, timber harvests, and fuel treatments on public and private lands throughout California. LANDFIRE FCCS maps are available depicting fuels in 2001, 2008, and 2014. We used shapefiles of wildfires, timber harvests, and fuel treatments on public and private lands to map disturbances in the period 2001-2018. These data were subsampled to train and validate a multinomial model predicting current FCCS category from the most-recent LANDFIRE-assigned FCCS category and disturbance history. The multinomial model was used to produce annually-updated statewide FCCS maps for every year from 2002-2018. To assess the value of annually-updated FCCS maps, we overlaid wildfire perimeters on the (out-of-date) LANDFIRE FCCS maps and our annually-updated maps. As a proxy for wildfire emissions, we summed the surface fuel load for all pixels within each wildfire, and compared the per-wildfire and per-year totals for different fuel maps.

Results

We produced annually updated fuels maps, which depict wildland fuels across California at a 30m resolution. These maps incorporate the effect of disturbances on wildland fuels, and were a substantial improvement over the current EES, which relies on legacy map depicting fuels as of 2001. The annually updated fuel maps provided a much smaller benefit over an infrequent-update strategy relying on official LANDFIRE updates. A literature review (and associated calibration of our fuel maps) indicated that bias inherent in the FCCS classification system is potentially a major source of bias in emissions estimates.

Conclusions

The annually-updated FCCS maps depict wildland fuels throughout California at a 30m resolution in a format readily usable by CARB's existing Emissions Estimation System. These maps reflect the effects of wildfires, timber harvests, and fuel treatments on wildland fuels. More importantly, the methods used to generate the annual updates can readily be applied to generate ongoing updates as new disturbance data become available. This will give CARB and researchers up-to-date information on wildland fuels throughout California. Further consideration should be given to the bias inherent in the FCCS classification system, which may be causing CARB to systematically over-estimate emissions from wildfires.

Body of Report

Introduction

Background

In the 21st century, California's government is moving to address the inter-related challenges of global warming and disrupted wildfire regimes. Aboveground plant biomass is a major carbon stock in California (Hurtt et al. 2002, Gonzalez et al. 2015), but the stability of biomass stacks is threatened by changing wildfire regimes (Westerling et al. 2011, Westerling 2018). Wildfires move carbon from biomass to the atmosphere (Kashian et al. 2006, Eskelson et al. 2016, Landry and Matthews 2016) and can negatively impact air quality and public health. The Californian government has recognized the importance of air quality and net carbon exchange (CARB 2017, FCAT 2018, CARB et al. 2019), and the California Air Resources Board (CARB) is responsible for maintaining a statewide inventory of greenhouse gas (GHG) and criteria pollutant emissions from a variety of sources, including wildfires.

To accomplish this task, CARB and its partners have developed the Emissions Estimation System (EES). The EES was originally built as ArcGIS plugins, and today exists as a set of python scripts. The system has been iterated on several times since its creation (Scarborough et al. 2001, Clinton et al. 2003, Wilkin et al. 2018), but the general function has remained consistent:

1. Overlay fire perimeters on statewide maps of vegetation or fuel types
2. Translate the mapped vegetation or fuel categories to inputs for the First Order Fire Effect Model (FOFEM; Keane 2016)
3. Pull fuel moisture data from the Wildland Fire Assessment System (Wilkin et al. 2018)
4. Insert the fuel and fuel moisture data into FOFEM, perform a batch run, and aggregate the per-pixel emission estimates for each burned pixel to get fire-wide estimates
5. Perform some post-processing to generate estimated emissions for additional pollutants not produced by FOFEM

The current version of EES uses Fuel Characteristic Classification System (FCCS) maps produced by LANDFIRE and the Fire and Environmental Applications Research Team to characterize surface fuels into stylized surface fuel models (Ottmar et al. 2007). Starting with the 2008 LANDFIRE Refresh project, the LANDFIRE program began updating their data products using a synthesis of remotely sensed disturbance, partner-contributed spatial data describing disturbances, and Forest Vegetation Simulator-based post-disturbance recovery (Nelson et al. 2013). Members of the Fire and Environmental Applications Research Team have assigned each FCCS fuel type a specific set of FOFEM-compatible fuel loading metrics. Previous research has shown that, of the fuel classification systems available in FOFEM, the FCCS maps most accurately predict pre-wildfire fuel loads and wildfire consumption (Lydersen et al. 2015).

Problem Statement and Project Goals

To estimate wildfire emissions, CARB's Emissions Estimation System (EES) uses the FCCS rasters from LANDFIRE to generate fuel load inputs for FOFEM runs. These FCCS rasters are updated semi-regularly by the official LANDFIRE version updates. The major updates (those including FCCS layers) describe fuels as of 2001 (LF 1.0.5), 2008 (LF 1.1.0), and 2014 (LF 1.4.0). Version releases lag behind the years they depict: LF 1.0.5 and LF 1.1.0 were released in 2011, and LF 1.4.0 was not available until 2017. LF 2.0.0 will include disturbances through 2017, with an estimated release date of 2020. An opportunity for easy gains in accuracy and precision of EES estimates would be to use the most recently available LANDFIRE layer (currently 2014) rather than relying on the legacy 2001 layer. However, even the most recently available maps are always several years out of date. Disturbances (such as wildfire or timber harvest) alter surface fuel conditions rapidly, which is likely a source of error in the EES emissions estimates if these areas burn before the FCCS map updates.

In response to this situation, CARB and UCB are collaborating on a project with three tasks:

1) Identify areas of demonstrable fuel transitions caused by fire, timber harvest, and large-scale tree mortality in forests.

2) Develop likely pathways and timing for fuel change following fire, timber harvest, and large-scale tree mortality.

3) Generate a report and manuscript that conforms to CARB's "Final Report Format" as described in 15-AQP007 Exhibit A1.

This Final Report describes the development of data products intended to improve the accuracy of CARB's wildfire emissions, by updating the official LANDFIRE FCCS maps to reflect the influence of disturbances.

Methods and Materials

Code, data files, and documentation associated with this project are available in the *fccs_predict* repository. This repository includes large spatial data files and is difficult to share over the internet, but code is archived on a private github repository. The entire repository, with code, source data, intermediate data, and data products, will be made available to CARB. The code and files are the ultimate authority on the methods for this project, but an outline of the processes is given below. Data preparation and analysis were performed in a combination of ArcGIS 10.6 and R Version 3.5.0. Processes relying on ArcGIS 10.6 were recorded as ModelBuilder objects, and the project repository includes the processes as both .tbx and .py files for each.

Source Data

This project relies on source datasets from three sources: LANDFIRE, CALFIRE's Fire and Resource Assessment Program (FRAP), and the United States Forest Service Region 5 GIS team (USFSR5). Data to describe fuels are drawn from the LANDFIRE FCCS rasters for 2001, 2008, and 2014 and the associated FCCS-FOFEM crosswalk table. (Note that there was a slight classification system change between 2008 and 2014.) For the purposes of this project, we treat the LANDFIRE FCCS rasters as correct: we tried to predict updated LANDFIRE maps, not predict the fuel loading number directly. LANDFIRE maps fuels at a nationwide scale and 30m resolution. This is an ambitious task and the LANDFIRE team has contributed a valuable and unique dataset, but the literature indicates that there are significant issues with the accuracy and precision of the fuel loadings described by LANDFIRE's FCCS maps (see Results below).

To describe disturbances, we used data from FRAP and USFSR5. Timber harvests on state and private lands were described using shapefiles of approved Timber Harvest Plans (THPs) and Non-Timber Management Plans (NTMPs). CALFIRE does not track implementation (or lack thereof) of THPs and NTMPs, so we were forced to assume that each harvest was implemented in the year the permit was issued. (The final model relied on 'disturbances since the last LANDFIRE refresh', so this assumption is less problematic than it would be if 'time since disturbance' was used as an explanatory variable.) Fuel treatments on state and private lands were described using CalMapper's supplemental activities layer. Wildfire perimeters were drawn from FRAP's fire perimeters layer, which includes fires on state, private, and federal lands. Data describing timber harvests and fuel treatments on federal lands are drawn from the USFS Region 5 Regional Activities dataset (FACTS). To reduce the number of terms in the multinomial model, we generalized the detailed activity categories from FACTS as either harvests or fuel treatments.

For this project, we did not draw upon the DISTYEAR product produced by LANDFIRE, which provides information about disturbances in annual 30m rasters. An important deliverable for this project is a method to predict *future* FCCS maps, so that CARB can model wildfire emissions in advance of the official (and slow) LANDFIRE updates. DISTYEAR likely provides a more complete description of disturbances, but the LANDFIRE team only provides updated DISTYEAR maps alongside the updates to their other data products. A process for predicting FCCS maps in advance of the official LANDFIRE updates thus cannot rely on the DISTYEAR data product.

Preprocessing Data

First, all disturbance and fuels data were clipped and transformed to a standard projection and extent in ArcGIS. Disturbances from various sources were aggregated into a single layer with standardized disturbance type and year coding. Then, for each year in the range 2002-2019, disturbances between the most recent LANDFIRE update (2001, 2008, or 2014) and the current year were selected and dissolved by spatial location. When multiple disturbances occurred in the same location, a combination category was used. Finally, the dissolved polygons were rasterized to create a single raster layer for each year, describing the disturbance history (since the last FCCS update) of each pixel. The disturbance rasters for each year were extended and masked so that all pixels outside California have the value NA and pixels inside California (but without a disturbance) have the value 'None'.

We separated the FCCS and disturbance rasters into two groups: First, the 'training stack' included LANDFIRE FCCS maps for 2001, 2008, and 2014 alongside the 'disturbances 2008' and 'disturbances 2014' rasters (which described disturbances from 2001-2008 and 2009-2014, respectively). These were used to fit and validate multinomial models, so we only include disturbance layers for 2001-2008 and 2009-2014. Second, the production stack included the three

LANDFIRE FCCS maps and disturbance-since layers for each year in the range 2002-2019. These data could be used with a fitted model to predict the FCCS layers for each year in the range. In practice, we only predicted fuels for 2002-2018, because the source data for disturbances in 2019 were incomplete at the time of analysis.

At 30m resolution and statewide extent, these rasters were too large (100+ Mb file size) to extract into local memory for fitting a model in R on a desktop machine. Instead, we subsampled the rasters, and used the subsamples to train and validate models. To test the effect of training sample size on the precision/accuracy of fitted model predictions, we pulled training samples of 1000, 5000, 10000, 20000, and 40000 points. These sample sizes are nominal rather than exact, because R samples from a rectangular bounding box and drops points outside the area of interest (California state boundaries). Actual sample sizes varied, but were approximately 70% of the nominal size. To test the effect of variation between training samples on precision/accuracy of fitted model predictions, we pulled 20 distinct samples of each size.

Fitting a Multinomial Model

First, each training sample was reformatted for use as explanatory variables in a model of the form:

$$FCCS_{current} \sim FCCS_{previous} + DISTURBANCE$$

Where:

- $FCCS_{current}$ is the FCCS classification for a single pixel in a specific ("current") year. Following the convention of the LANDFIRE FCCS maps, $FCCS_{current}$ reflects the effect of all disturbances *up to and including* the current year (*i.e.*, it depicts fuels as of December 31 of the current year). For example, the 2014 FCCS map depicts fuels *after* the 2014 King Fire.
- $FCCS_{previous}$ is the FCCS classification assigned to the pixel on the most-recent LANDFIRE FCCS map. For example, if $FCCS_{current}$ is the fuel category assigned as of December 31 2013, $FCCS_{previous}$ is the fuel category on the 2008 LANDFIRE FCCS map.
- $DISTURBANCE$ is a raster depicting the disturbance history of each pixel *since* $FCCS_{previous}$. It includes all disturbances which occured after the year of $FCCS_{previous}$ up to and including the year of $FCCS_{current}$. For example, if $FCCS_{current}$ is the fuel category as of (December 31) 2013, $DISTURBANCE$ will depict the disturbances from January 1 2009 through December 31, 2013. Disturbances were classified as wildfire, fuel treatment, or timber harvest. If more than one type of disturbance occurred on a pixel, then a combination category (e.g. harvest-wildfire) was assigned.

Because each location in the training sample had fuels data for 2001, 2008, and 2014, and disturbance data for 2002-2008 and 2009-2014, each location (pixel) provided two training samples. Given a training sample, the *multinom()* function from the R package nnet can fit a multinomial logistic regression model predicting $FCCS_{current}$ from $FCCS_{previous}$ and $DISTURBANCE$ (Venables and Ripley 2002). The softmax parameter estimation algorithm used by *nnet::multinom()* is not deterministic: It is possible to arrive at different parameter estimates given identical training data. However, sensitivity testing revealed that the parameter estimation is functionally deterministic: Multiple models fit on the same training sample produced estimates with nearly identical precision and accuracy (see Appendix). Sensitivity tests also compared models with and without an interaction term between $FCCS_{previous}$ and $DISTURBANCE$.

A dataset of explanatory variables can be fed into a fitted model to predict the response ($FCCS_{current}$) for each location. The multinomial model is unable to predict $FCCS_{current}$ for locations where the $FCCS_{previous}$ category was not included in the training dataset used to fit the model. For these locations, we assumed that $FCCS_{current} = FCCS_{previous}$ (no change since the most-recent LANDFIRE map).

Multinomial logistic regression models actually the probability of *each* separate FCCS category for each location (approximately 400 probabilities per location, most of which are near or equal to 0). We selected the most-likely FCCS category as the 'predicted' category for each location. In theory, it would be possible to assign surface fuel loads to each location based on a weighted average for each of the possible FCCS categories. For example, if a location has a 90% chance of being category A with 15 tons per acre of fine fuels, and a 10% chance of being category B with 100 tons per acre of fine fuels, we would assign it $(100 * 0.1) + (15 * 0.9) = 23.5$ tons per acre. This method would better reflect uncertainty about fuel type transitions, but would require very high computing power and/or time: For each year, instead of producing a single statewide predictions raster where the cell values correspond to most-likely FCCS category at each location, we would have to produce and process several hundred statewide rasters (one for every FCCS category represented in California), where cell values correspond to the probability of the category occurring at each location.

Validation and Sensitivity Testing

Two predictions were made for each cell: one for 2008 and another for 2014. We used the official LANDFIRE FCCS maps for 2008 and 2014 as validation datasets to evaluate the accuracy and precision of model predictions. A separate multinomial model was fit for each training dataset, with 20 training datasets per size class and sample sizes ranging from 1000 to 40000 points. Each model was tested against 19 validation datasets of 40000 points. Measures of error (misclassification rate, root mean square error fuel load, and root mean square error divided by mean actual fuel load) and bias (mean error, and mean error divided by mean actual fuel load) were calculated for each combination of model and validation dataset.

Currently, CARB does not have a way to generate annual updates to the FCCS maps, and must estimate wildfire emissions using whatever LANDFIRE map provides the most up-to-date information on fuels. For example, to estimate wildfire emissions for 2017 wildfires, the most-recent LANDFIRE map is for 2014. For each validation dataset, the same measures of error and bias were calculated for the 'predictions' implied by using the most recent LANDFIRE FCCS map instead of the predictive model. That is, we compared the predictions from our multinomial model to predictions from a simplified model where $FCCS_{current} = FCCS_{previous}$ for every cell. This is equivalent to copying the 2001 LANDFIRE map to 'predict' fuels in 2008, and copying the 2008 LANDFIRE map to 'predict' fuels for 2014. This allowed comparisons of the bias and precision of the predicted map against a realistic null case: the status-quo system.

Sensitivity tests were performed by repeatedly fitting and validating models. These tests explored:

1) **The effect of training sample size on model precision and accuracy.** Nominal sample sizes of 1000, 5000, 10000, 20000, and 40000 points, with 20 samples from each size category, were tested against 19 validation datasets of (nominally) 40000 points.
2) **The effect of repeated model fits on the same training sample.** Nominal sample sizes of 1000, 5000, 10000, 20000, and 40000 points, with five samples from each size category and five separate models fit from each sample were tested against four validation datasets of (nominally) 40000 points.
3) **The effect of including an interaction term between $FCCS_{previous}$ and $DISTURBANCE$ in the model.** Nominal sample sizes of 1000, 5000, and 10000 points, with five samples from each size class, were tested against four validation datasets of (nominally) 40000 points. Training sizes were limited to 10000 for this analysis because fitting a model with interaction terms was much more computationally intensive.

The results of these tests are described in more detail in the Appendix, but these general conclusions informed decisions about the final version of the prediction maps:

- Including an interaction term in the model provided little to no benefit, while adding substantial computational cost and limited maximum training sample size.
- Multiple fits on the same training data produced functionally identical models.
- Increasing training sample size yielded diminishing returns in terms of improved accuracy/prediction of the fitted models past ~10k nominal sample size.
- Different training samples (of the same size) did produce models with different levels of error/bias.

Scaling to Statewide Maps

To generate statewide maps of FCCS categories for each year in the range 2002-2018:

- Training sample *training_n040000_i02* was used to fit the multinomial model, because it was of the highest size class and produced the most accurate (least biased) model when used to predict fuel loads from the validation data sets.
- The final model was fit without an interaction term.

For each year in the range 2002-2018, the previous official LANDFIRE FCCS map (from 2001, 2008, or 2014) and the raster layer for disturbances since the previous update were fed to the model as mapped explanatory variable rasters, and used these to predict an FCCS map for the current year. Because of memory limitations, the R script produced tiled FCCS maps, which were mosaicked together in ArcGIS. The predicted FCCS statewide maps are rasters of 30m x 30m resolution at statewide extent, where each cell value corresponds to the predicted FCCS category for that year.

Deriving Surface Fuel Loads within Wildfire Perimeters

The ultimate purpose of these FCCS maps is to supply inputs for wildfire-affected surface fuels in batch FOFEM runs. We mimicked the current EES by overlaying wildfire perimeter polygons onto raster maps of FCCS categories. For each wildfire, the total number of pixels in each FCCS category was summed. Total tons of surface fuels affected by each wildfire was calculated by multiplying the number of pixels in each FCCS category by the pixel area (900 m^2, 0.22 acres) and the tons per acre of fuel represented by the FCCS category, and summing across all FCCS categories included in the wildfire perimeter. We also aggregated by year, giving annual totals of surface fuels affected by wildfire. We use the term 'affected' rather than 'burned' because in both FOFEM and reality less than 100% of the fuels will actually combust.

By overlaying wildfire perimeters on different sets of FCCS maps, we were able to compare three different mapping strategies. These were:

1. Overlay all wildfire perimeters on the official LANDFIRE FCCS map for 2001. This represents the current EES system, which relies exclusively on the legacy 2001 FCCS map.

2. Overlay all wildfire perimeters over the most recent official LANDFIRE map which would have been available at the time of the fire. For example: For a fire in 2010 we used the 2001 LANDFIRE FCCS map (the 2008 LANDFIRE map was not released until 2011), but for or a fire in 2013 we used the 2008 LANDFIRE FCCS map. This represents a mapping strategy based on using the "best available" LANDFIRE map, assuming that wildfire emissions are estimated the same year the wildfire occurs.

3. Overlay all wildfire perimeters on the annually-updated FCCS maps produced by this project. Fires were overlaid on the annually-updated FCCS map for the year before the fire (e.g., for a fire in 2013 we would use the 2012 predicted FCCS map, which includes the effect of disturbances during 2012). These fuel estimates represent a strategy based on annually updating the FCCS map using the predicted maps generated for this project.

The annual surface fuels affected by wildfire for each mapping regime were plotted to assess the added value of each mapping scheme against the status quo (strategy 1 above).

Calibrating Surface Fuel Loads

Limited accuracy and precision of the FCCS system itself is potentially a significant source of error and/or bias in EES emission estimates. Keane et al. (2013) used spatially-explicit FIA plot data to validate the fuel loads described by various mapped data products, including LANDFIRE's FCCS maps. Their results indicate that error and bias in the FCCS-FOFEM crosswalk are likely a significant source of error and bias in CARB's wildfire emissions estimates. In general, Keane et al. (2013) found that the FCCS categories tend to over-predict the real-world fuel loads, especially when the FCCS category describes a high fuel load (Table 1). They also found that the FCCS maps do not predict fuels precisely; *i.e.* there is a lot of variation in FIA-observed fuel load within a given FCCS category.

Fuel Component	R^2	Slope	Intercept	% Bias	RMSE (kg / m^2)
Duff	0.03	0.02	1.42	811.4	22.54
Litter	0.02	0.15	0.83	39.8	1.46
FWD	0.04	0.05	0.33	612.1	3.80
CWD	0.12	0.08	1.10	356.7	11.4
TSFL	0.13	0.06	3.39	474.8	35.51

Table 1 (Reproduced Table 7 of Keane et al. 2013):

Comparison of the mapped classification class loadings for the FCCS classifications to the reference FIA-measured surface fuel component loadings using regression and error statistics. Ideally, R^2 and slopes should be close to 1.0, intercepts should be zero, % bias should be zero, and Root Mean Square Error (RMSE) should be zero. Surface fuels are described in the Glossary of Terms, Abbreviations, and Symbols.

Using the summary statistics reported by Keane et al. (2013), we calibrated the per-wildfire and per-year fuel load estimates generated using our annually-updated FCCS maps. Two independent calibration methods were applied:

1. **Linear regression:** We calibrated the FCCS-FOFEM crosswalk table (which gives fuel component loadings for each FCCS category) using the linear regressions parameters given in Keane et al. (2013) Table 7. The calibrated crosswalk gives the mean FIA-observed fuel component loadings for each FCCS class. The calibrated crosswalk was then used to calculate the total wildfire-affected surface fuels for each year as described above. This method produced a single calibrated estimate for wildfire-affected surface fuels for each year, so it only allows us to assess accuracy, not precision. However, adjusting the FCCS-mapped fuel loads based on the linear regression results is straightforward, and doing so allows us to validate our second calibration approach.

2. We used the results of the **error analysis** reported in Keane et al. (2013) to back-calculate the sample mean FIA fuel load for each FCCS-mapped fuel load. Using the standard error of sample means, we drew a potential population mean FIA fuel load from a normal distribution with the proper mean and variance. Repeated several times, this allowed us to use the results from Keane et al. (2013) to estimate a distribution of real-world fuel loads associated with each FCCS category, incorporating both bias and error in the FCCS assigned fuel loads. This method produced a range of calibrated estimates for the wildfire-affected surface fuels for each year.

We compared our calibrated estimates for the total wildfire-affected surface fuel load in each year against estimates produced using the standard FCCS-mapped fuel component loadings currently used by the EES.

Results

Model Predictions

The resulting multinomial model predicts the current FCCS category for a pixel based on the last-known FCCS category and the disturbance history. The model actually uses FCCS class ID as a categorical variable, but mapping the FCCS classes to their associated total surface fuel load helps visualize the patterns of the predictions (Figure 1). Most combinations of pre-disturbance FCCS category and disturbance result in reduced post-disturbance surface fuel loads, though there are exceptions. In reality, surface fuel loads may increase post-disturbance as a result of needle-cast, falling snags, and/or tree mortality. For the statewide maps, where a pixel's previous FCCS classification was not described by the multinomial model, we assigned the current FCCS class to be the same as the previous (*i.e.*, we used the out-of-date map value for that pixel).

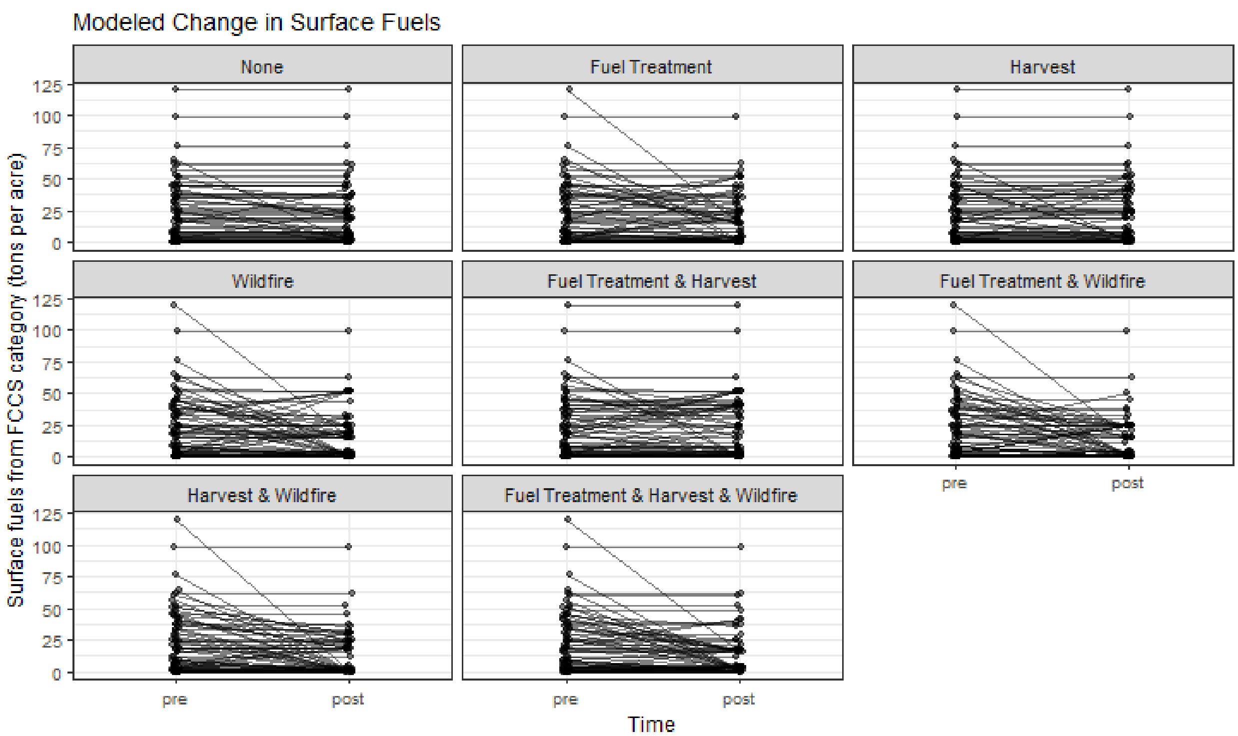

Figure 1: Modeled Transitions in total surface fuel load

Statewide FCCS maps and Mapped Fuel Loads

Rasters of predicted FCCS categories for each year were generated and provided to CARB. We produced a separate fuels map for each year from 2002-2018. Following the LANDFIRE convention, each year's map depicted fuels on the last day of that year. For example, the fuels map for 2015 incorporated the effects of all disturbances up to and including December 31, 2015.

Improved Fuels Estimates

The purpose of the FCCS maps is to overlay them with wildfire polygons and extract the area of each FCCS category affected by the fire. Each FCCS category maps to a specific set of FOFEM inputs, which EES can use to produce per-category emissions estimates, which would then be scaled by the acreage for each category and summed across the entire fire to produce a per-fire emissions estimate. The effect of our predicted maps on emissions estimates could not be directly described without completely reproducing EES (including the complex fuel moisture mapping system). However, the affected fuel loads for each fire provided a reasonable proxy: where an out-of-date fuels map predicted much higher affected fuel loads than an updated map, it is reasonable to expect that the outdated map would predict higher emissions from FOFEM.

Summing the total affected fuels for each wildfire allowed comparison of three potential mapping strategies. The first strategy represented the EES status-quo, and used the LANDFIRE 2001 FCCS layer to describe fuels for all wildfires. The second strategy relied on the best-available LANDFIRE map for each fire year. LANDFIRE issued updated maps depicting fuels as of 2008 and 2014, but these updates were not available until 2011 and 2017 (respectively). Finally, the third strategy used the annually-updated maps produced by this project. As expected, the total tonnage of surface fuels affected by each wildfire was log-normally distributed, with most fires affecting 10 to 1000 tons of surface fuels and a small subset of very-large fires affecting 100,000+ tons of surface fuels (Figure 2). The tonnage distributions were similar across all three strategies.

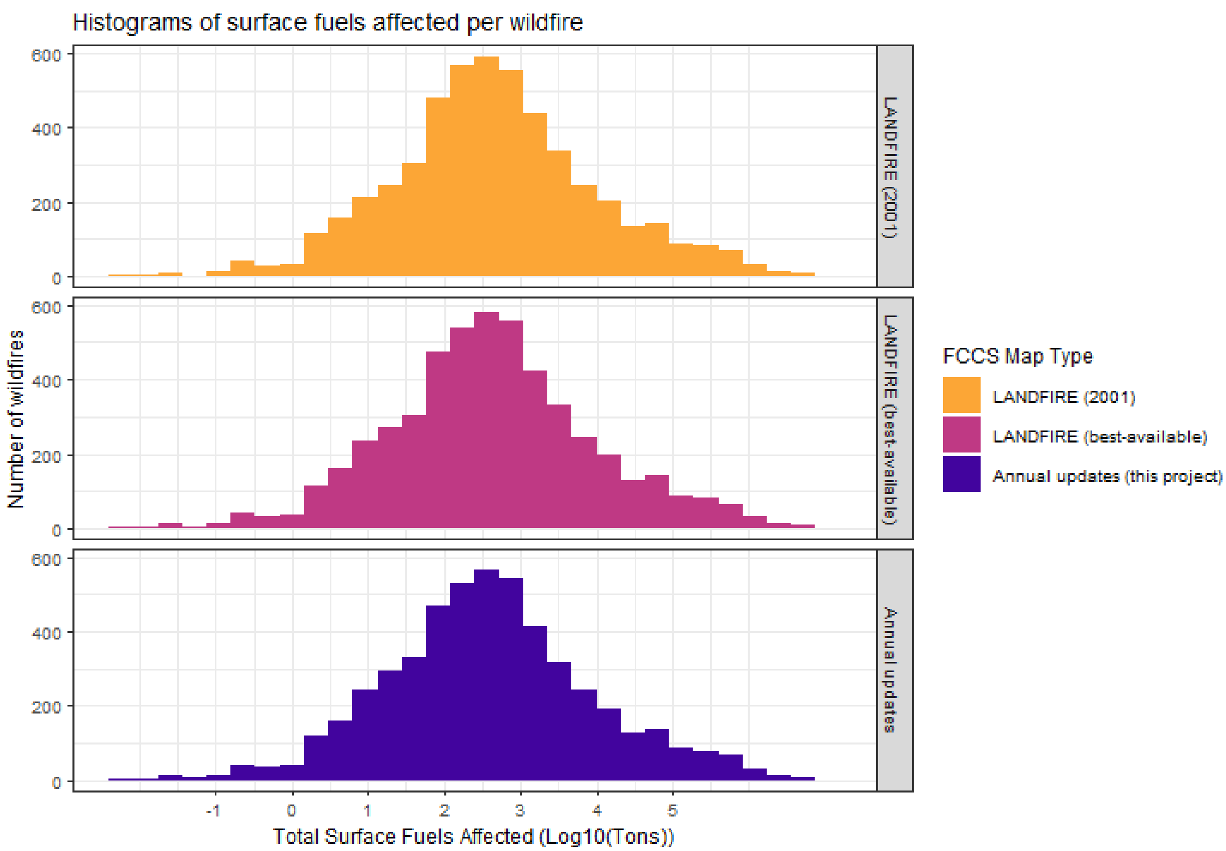

Figure 2: Histograms of surface fuels affected per wildfire

Individual wildfire perimeters were overlaid on fuels maps, selected according to one of three strategies. The area of each FCCS category within each wildfire was calculated and multiplied by the total surface fuel load associated with each FCCS category, producing an estimate of the total surface fuel load within each wildfire footprint.

Matching the estimates from the LANDFIRE maps and the predicted maps by fire ID (Figure 3) makes it clear that repeat disturbances between LANDFIRE updates were very rare. Limited additional value was added by updating the FFCS maps more frequently than LANDFIRE does. However, Figure 3 also shows that the both annual updates and the best-available strategy provided major improvements over an exclusive reliance on the legacy 2001 LANDFIRE map. Summing the wildfire-affected fuels by year (Figure 4) supported these conclusions: the effect of predicting annual updates to the FCCS maps was small, relative to the effect of LANDFIRE's less frequent updates. However, divergence between the best-available LANDFIRE and our predicted maps increased in 2017 and 2018. This suggests that the 2014 LANDFIRE map is approaching the end of its effective lifespan.

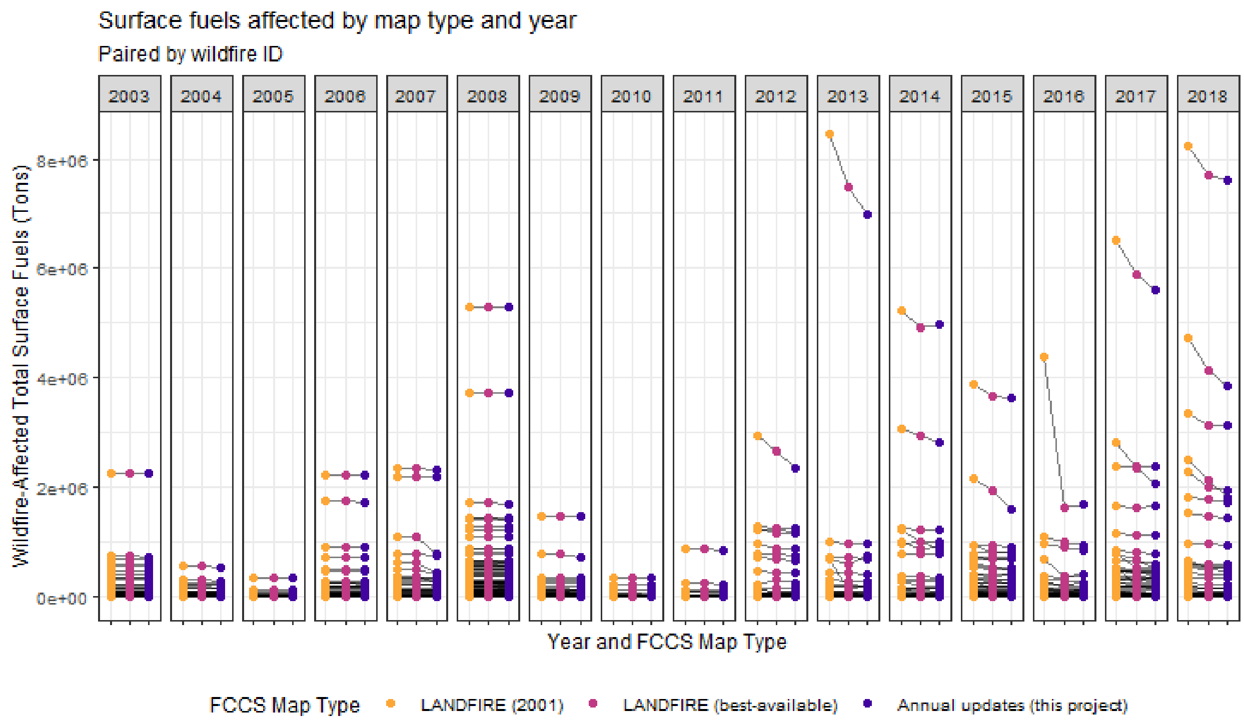

Figure 3: Comparing mapping strategies for individual wildfires

Estimates of the total surface fuel load affected by each wildfire were generated using each mapping strategy. The resulting estimates are grouped by year and wildfire.

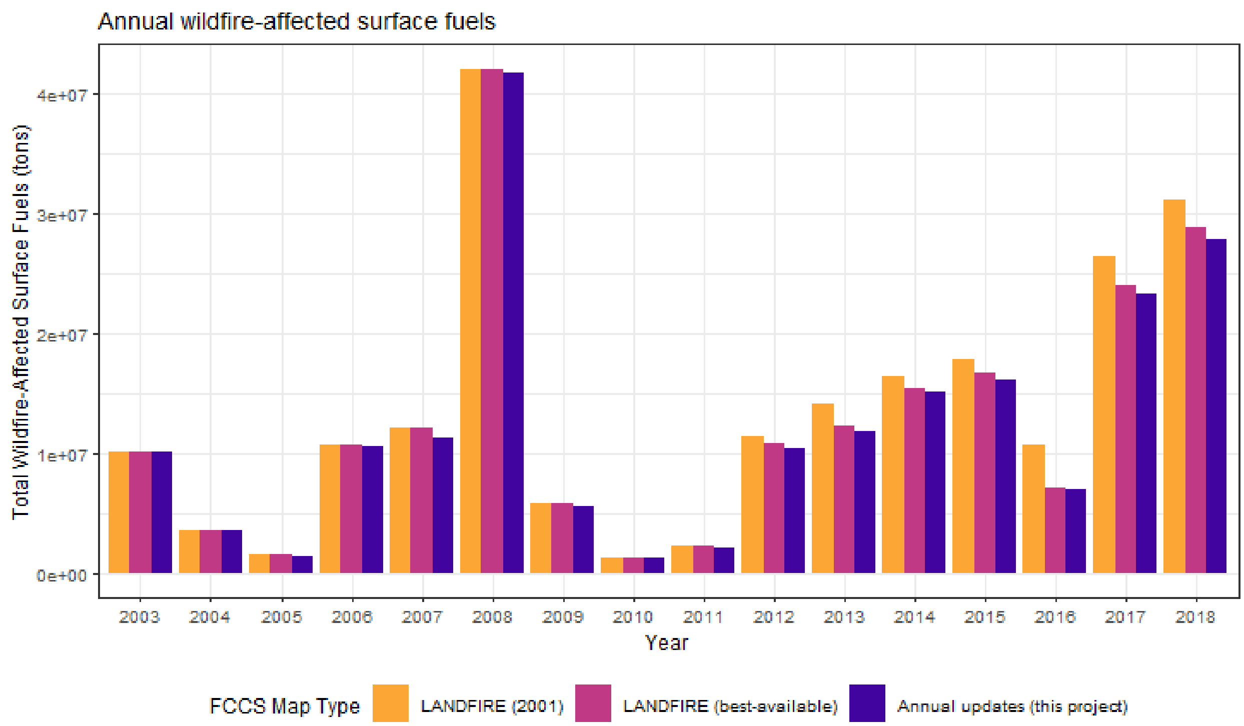

Figure 4: Comparing mapping strategies for annual totals

Estimates of the total surface fuel load affected by each wildfire were generated using each mapping strategy. The resulting estimates are summed by year of fire occurrence.

Calibrating fuels estimates

Both of the independent calibration methods showed that the uncalibrated FCCS fuel component loadings greatly overestimated the total surface fuels affected by wildfire (Figure 5). The bias was approximately an order of magnitude: the FCCS classification system predicted total surface fuel loads nearly 10 times greater than they actually were, according to real-world FIA plots. Both calibration methods produced very similar findings, increasing our confidence in this interpretation. This was expected, based on the findings of Keane et al. (2013). By contrast, the small magnitude of variance introduced by error analysis 2 came as a surprise. The findings of Keane et al. (2013) indicate that the FCCS categories introduce a large amount of error, as well as bias. However, this per-pixel error had little effect when averaged over the many 900 m^2 pixels within large wildfire.

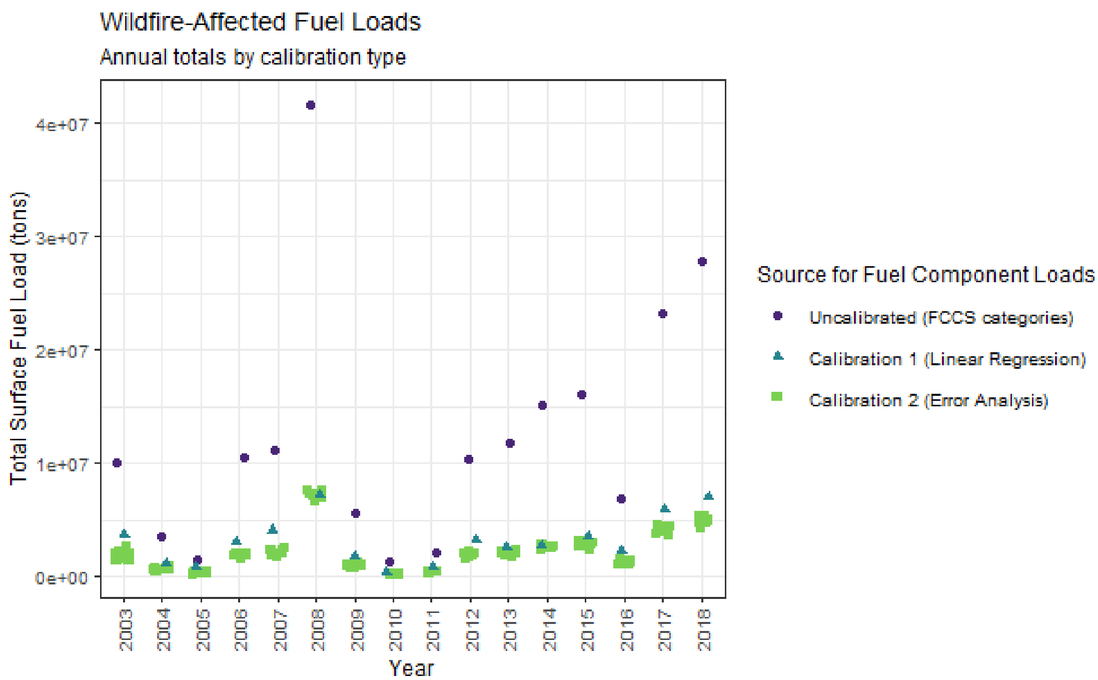

Figure 5: Calibrated vs. uncalibrated annual totals

Individual wildfire perimeters were overlaid on the annually-updated fuels maps. The area of each FCCS category within each wildfire was calculated. Per-acre surface fuel loads for each FCCS category were assigned in one of three ways. The uncalibrated fuel loads use the standard FCCS-FOFEM crosswalk values. These crosswalk values were calibrated using either a linear regression or the error analysis summary statistics, as reported by Keane et al. (2013). The error analysis calibration incorporates stochastic error in the crosswalk values, so it was repeated 10 times to produce a distribution of fuel load estimates. The per-acre fuel load estimates were multiplied by the total surface fuel load associated with each FCCS category within each wildfire, producing an estimate of the total surface fuel load within each wildfire footprint. The per-wildfire totals were then summed to produce annual totals, which are presented here.

The findings of Keane et al. (2013) indicate that the FCCS categories are more accurate and precise for some fuel components than others, and our calibrated values reflected this (Figure 6). Our calibrated wildfire-affected fuel loads for litter were similar to the default uncalibrated values. The vast majority of the FCCS categories' bias in total surface fuel loads was due to over-estimated duff and coarse woody debris fuel loads.

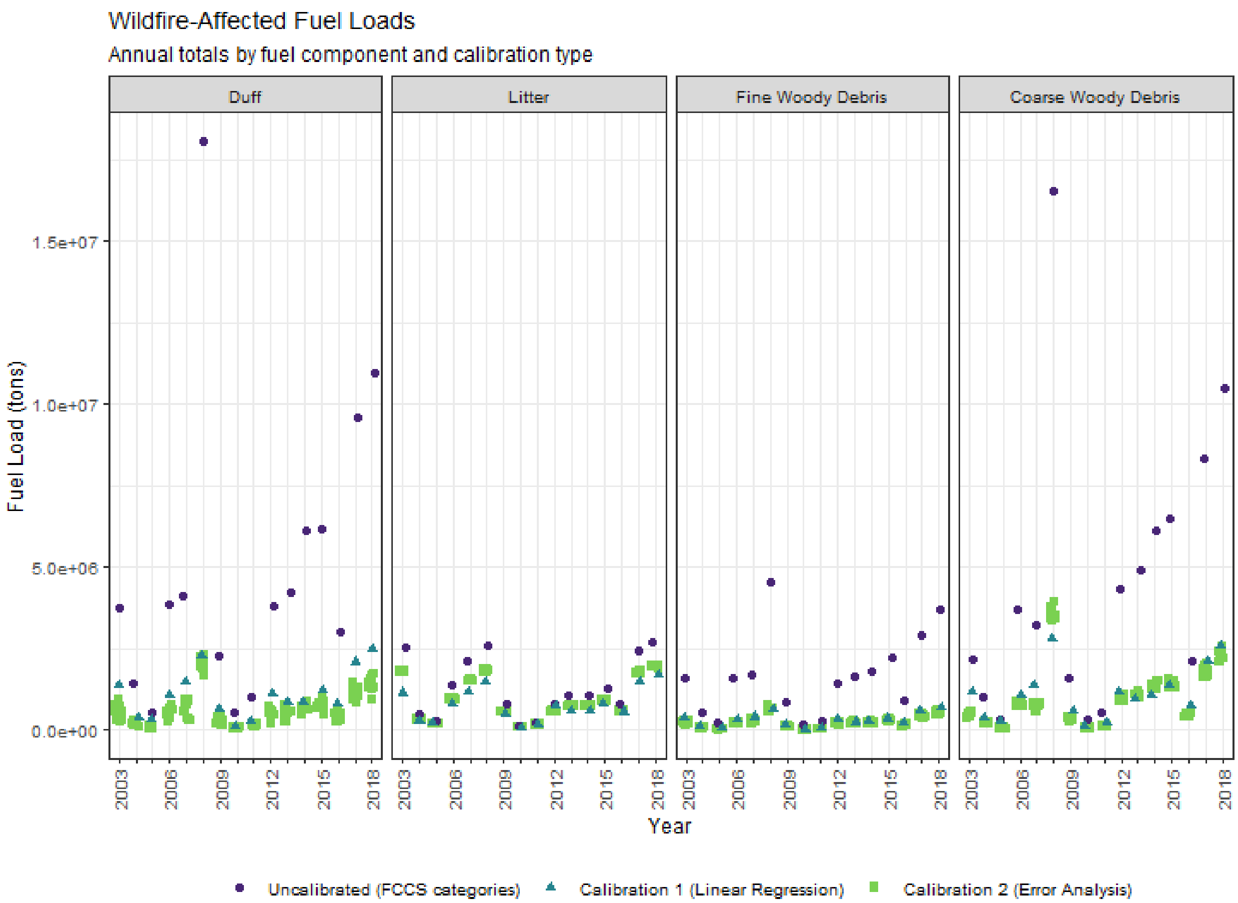

Figure 6: Calibrated vs. uncalibrated annual totals (fuel components)

See Figure 12 for details. This figure breaks the total surface fuel load for each year down into totals for duff, litter, fine woody debris, and coarse woody debris. See the Glossary for explanation of terms.

Discussion

This project implemented an ambitious goal: producing annually updated statewide fuels maps at 30m resolution across a variety of disturbance and ecosystem types. These maps are provided to CARB as the deliverables for Tasks 1 and 2 of this project, and this report concludes Task 3. The annually-updated maps offer a substantial improvement in accuracy over the status-quo EES system, which relies on a single legacy LANDFIRE FCCS raster depicting fuels as of 2001. However, we also found that the EES system could be substantially improved by utilizing the best-available official LANDFIRE maps. LANDFIRE's official updates, which are now released approximately every 6 years, also incorporate the effect of various disturbances on wildland fuels. Wildfires in California rarely overlap with disturbances which have happened since the most-recent LANDFIRE FCCS map, partly due to the self-limiting effects wildfires have on fuels (Collins et al. 2009). Our results establish that the 2001 LANDFIRE map is clearly out of date, and should not be used to describe wildland fuels in the late 2010s.

We also applied the results of a ground-truth validation of the FCCS classification system (Keane et al. 2013) to calibrate the fuel loads depicted by our annual FCCS maps. Both of the independent calibration methods indicated that the FCCS classification system over predicts fuel loads to a large degree. The amount of error introduced by the FCCS classification system was small relative to the amount of bias. Further, we note that wildfire-affected fuels are not the same thing as predicted emissions: not all of the fuels within a wildfire's footprint will actually be consumed and released as emissions. The FCCS system is most accurate in describing litter and fine woody debris loads, which are often the most completely consumed fuel components across a range of fire severities (Campbell et al. 2007, Lydersen et al. 2015). Another study ground-truthing the FCCS classification system (Lydersen et al. 2015) found that the FCCS classification system produces more accurate and precise emissions estimates from FOFEM than alternative fuel characterization systems available within FOFEM. It is possible that the FCCS characterization system is better at producing accurate and precise emissions estimates than it is at describing plot-level fuel loads, but Lydersen et al. (2015) note that bias in mapped fuel loads is strongly correlated with bias in emissions estimates. Our calibrated fuel load estimates for each wildfire could be propagated through the entire EES to produce calibrated emissions estimates for comparison.

Earlier iterations of the project used a model of the form:

$$FCCS_{current} = FCCS_{previous} + MOSTRECENTDISTURBANCE + YEARSSINCE$$

The model was simplified for several reasons. First, the term for years since disturbance was not significant during testing. More importantly, using only the most recent disturbance tended to mask the effects of earlier disturbances: a timber harvest after a wildfire is not the same as a timber harvest with no wildfire. Simplifying the model streamlined the processing of the disturbance history rasters and allowed the model to account for multiple overlapping disturbances between LANDFIRE updates. However, the final model excluded any effect of time since disturbance, and did not (directly) model recovery after disturbance. LANDFIRE releases official updates (which do reflect recovery) approximately every 6-7 years, so on average a cell would only have 3.5 years of un-modeled recovery after disturbance. Eskelson and Monleon (2018) found that on this time scale, duff loads did not change from their immediate post-fire levels (Eskelson and Monleon 2018), but that litter loads increased by 7% per year (though from a very low initial level). They found that fine woody fuels increased at a constant rate of 6-40% per year and coarse woody fuels at 6-48% per year, depending on fire severity and forest type. In this context, the omission of time since disturbance from our model is only a minor limitation.

A more significant limitation is with our calibration approach using the findings of Keane et al. (2013). Presumably, some FCCS categories describe fuels more accurately and/or more precisely than others. With access to the FCCS-labeled FIA plot data used by Keane et al. (2013), it would have been possible to fit a separate calibration for each FCCS category, rather than two calibrations for the entire system. Unfortunately, the authors of Keane et al. (2013) were unable to share their source data (FCCS-labeled FIA plots) because of the sensitive nature of spatially-explicit FIA data (Forest Inventory and Analysis 2019). Without the source data, this study was forced to rely on summary statistics. In addition, it is important to note the scale mismatch between FIA plots, FCCS pixels, and wildfire footprints (Keane et al. 2012, Keane 2016). The calibration analysis presented here applies summary statistics which were calculated using 1-20m fuels transects and 900 m^2 plots to calibrate fuel load estimates for wildfires which may span 100,000 hectares. We applied fine-scale plot sampling to validate medium-scale data products which are used to describe landscape-scale processes, but propagation of error and bias across scales is poorly understood (Keane 2013).

These findings highlight the difficulty of creating a unified system to predict wildfire emissions across the entire state of California. Interactions between wildfire, fuels, and weather are highly complex and occur at multiple scales (Liang et al. 2017, Stevens et al. 2017). Ground-truthed data on fuels and/or wildfire emissions are time-consuming and expensive to collect (Keane et al. 2013, Lydersen et al. 2015). Efforts to quantify the spatial and temporal variability of wildland fuels are still being developed and many have yet to be applied in the California context (Dunn and Bailey 2015, Keane 2016, Blomdahl et al. 2019). There are complex feedbacks between disturbance and forest structure, which interact in complex ways and at multiple scales (Page et al. 2014, Coppoletta et al. 2016, Tiribelli et al. 2018, Levine et al. 2019). Accurately and precisely estimating wildfire emissions across California is an ambitious goal.

Summary and Conclusions

The existing Emissions Estimation System (EES) used to estimate wildfire emissions across California relies on a Fuel Characteristics Classification System (FCCS) map produced by the LANDFIRE team to describe the type and amount of fuels affected by each wildfire. However, the existing EES uses a static map of fuels across the state from 2001. In reality, disturbances such as wildfire will dramatically change wildland fuels, and so the legacy 2001 FCCS map has become increasingly out-of-date. This resulted in EES over-estimating the surface fuels involved in a wildfire, particularly when the wildfire overlaps a prior disturbance. This project (15AQP007) sought to address this deficiency, and was broken into three tasks:

1) Identify areas of demonstrable fuel transitions in forests

2) Develop likely pathways and timing for fuel changes in forests

3) Report and manuscript that conforms to the "Final Report Format" described herein

To address tasks 1 and 2, we developed an algorithm to generate annually-updated FCCS maps. Our annually-updated maps are provided alongside the documentation, intermediate data products, and scripts used to produce them. We provide a separate fuels map for each year from 2002-2018. Following the LANDFIRE convention, each year's map depicts fuels on the last day of that year. (The map for 2015 incorporates the effects of all disturbances up to December 31, 2015.) This report fulfills Task 3.

We assessed the efficacy of our fuels maps by overlaying wildfire perimeters. This allowed us to compare the fuel load estimates from our annually-updated maps against two competing fuels-mapping strategies: the status-quo strategy relying on legacy 2001 LANDFIRE FCCS map, and an alternative strategy relying on the best-available LANDFIRE FCCS map. (Updates to the LANDFIRE maps are released approximately every 7 years.) Our annually-updated maps provide a major improvement over the legacy map, and minor improvements over the best-available maps.

The literature review conducted for this project indicated that there may be substantial biases inherent in the FCCS classification system itself, independent of any attempt to update the maps. We used the relevant literature to calibrate fuel loading estimates for wildfires across California, and found evidence to suggest that the EES is dramatically over-estimating the amount of biomass affected by wildfires each year. Future iterations on the calibration protocol described here could substantially improve the accuracy of CARB's emissions estimates, but more study is needed.

Recommendations

The existing EES performs admirably, given the difficulty of the task. Using the annually-updated maps generated by this project instead of the legacy 2001 LANDFIRE map will dramatically improve emissions estimates. The algorithm to generate the annual updates could be improved in several ways, such as modeling time since disturbance, explicitly incorporating spatial the spatial relationship between pixels, and including different levels of fire severity as different disturbance types. All of these improvements would have a sound ecological basis (Hessburg et al. 2016). However, they are likely to provide only marginal improvements to the accuracy and precision of the fuels maps used by EES. Indeed, most of the benefits provided by our annual updates can be achieved by relying on the official LANDFIRE refresh maps, which are released approximately every 6-7 years and also incorporate disturbance-driven transitions in fuel type. Repeat disturbances within a short timeframe are a relatively rare event, and further improvements in mapping disturbance transitions are unlikely to provide substantial benefits to emissions estimates.

Because the FCCS classification system tends to over-predict fuel loads, even completely up-to-date maps may be dramatically over-predicting the total tonnage of wildland fuels affected by wildfire each year. This over-estimation of wildland fuels is likely biasing emissions estimates (Lydersen et al. 2015). Improving the accuracy and precision of predicted fuel loads is a complex but important problem. This project introduces a rough calibration approach using summary statistics derived from a large empirical dataset. In the future, calibrations could be dramatically improved by incorporating the source data used for Keane et al. (2013), and the effect of these calibrations on FOFEM emissions estimates should be explored. Careful consideration will need to be given to the spatial scope of the problem (landscape-scale wildfires), the data products (statewide rasters at 30m resolution) and the source fuels data (highly-local fuel transects).

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List of inventions reported and copyrighted materials produced

None.

Glossary of Terms, Abbreviations, and Symbols

CARB: The California Air Resources Board.

CWD: Coarse woody debris – dead and down woody materials greater than 3” in diameter. Synonymous with 1000-hour fuels.

EES: The Emissions Estimation System. An integrated set of tools and used by CARB to estimate emissions of pollutants and greenhouse gases from wildfires.

FCCS: The Fuel Characteristics Classification System (Ottmar et al. 2007). A categorical system describing wildland fuels across the United States, using several hundred different categories. Each category is associated with a set of parameters (e.g. the litter fuel load) which can be used as inputs for FOFEM.

FIA: The Forest Inventory and Analysis Program. A nationwide sampling network operated by the US Forest Service. See https://www.fia.fs.fed.us/.

FOFEM: The First Order Fire Effects Model (Keane2016). Software used to estimate wildfire emissions.

FRAP: The Fire and Resources Assessment Program. A branch of CALFIRE focused on assessing natural resources and wildfire risk. FRAP generates and distributes many important geo-spatial data products for California.

FWD: Fine woody debris – dead and down woody materials less than 3” in diameter. Synonymous with 1-hour, 10-hour, and 100-hour fuels (summed).

NTMP: A non-timber management plan. Regulatory alternative to a THP available in some circumstances.

THP: Timber harvest plan. Formal documentation of a plans to implement a timber harvest, which must be submitted to (and approved by) the California Board of Forestry.

Total surface fuel load: The total amount of dead biomass on the ground surface. In this report, total surface fuel load is the sum of the load of duff, litter, coarse woody debris, and fine woody debris.

Appendix:

Sensitivity Test Results

Only a selection of the sensitivity test results are described and shown below. For complete results see the file *03-sensitivity_test_results.Rmd*, which presents more figures comparing misclassification rates, root mean square error as a percent of mean fuel load, and mean error as a percent of mean fuel load.

Interaction Terms

Including an interaction term did not consistently improve model precision or accuracy (Figure 7). We also ran significance tests which indicated that including an interaction term significantly increased root mean squared error (*p=0.012*) and did not significantly improve prediction accuracy. Including an interaction term also comes with a cost: The high computational demands of fitting models with interaction terms restricts the maximum possible size of the training sample, due to memory limitations. Given these findings, we opted not to include an interaction term in the production version of the model.

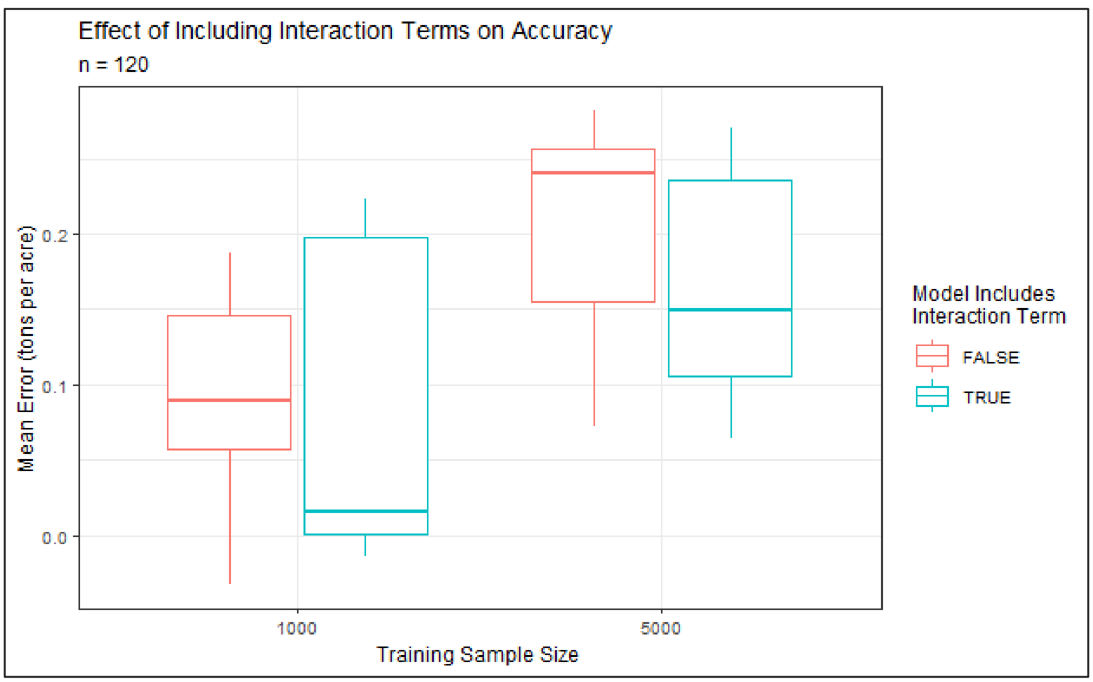

Figure 7: Effect of an interaction term on model accuracy

Sample Size

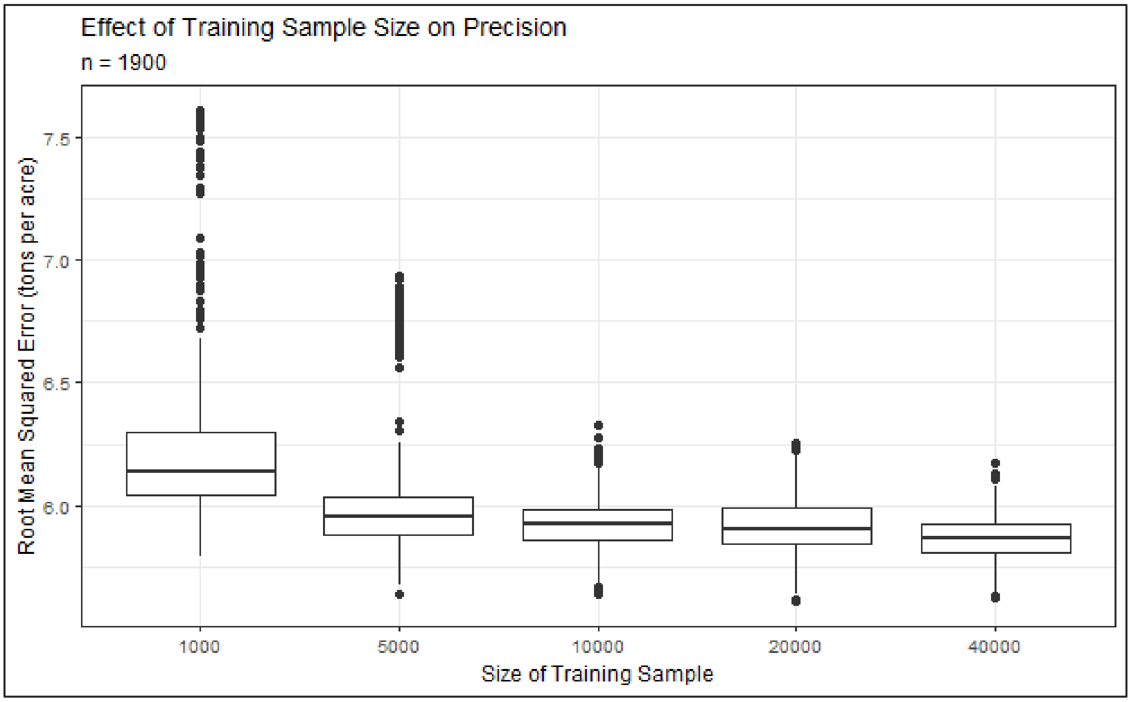

Figure 8: Effect of training sample size on model precision

Increasing the training sample size did increase the precision of the fitted models, but with decreasing returns (Appendix and Figure 8). Going from a (nominal) training sample size of 1000 to 5000 points reduces median RMSE by approximately 1 ton per acre, but going from a (nominal) size of 20000 to 40000 reduces median RMSE by less than 0.05 tons per acre. Increasing sample sizes do not appear to reduce median bias (mean error), but they do reduce the between-model variance in bias, making different training samples behave more consistently (Appendix). We conclude that increasing the nominal sample size beyond 40,000 points is unlikely to yield substantial increases in the precision or accuracy of predictions.

Multiple Fits

The softmax fitting algorithm used by the R function *nnet::multinom()* to fit a multinomial model is not deterministic (Venables and Ripley 2002). Separate fits on the same training data may converge to different parameter estimates because of random starting values. In order to test the effects of this on the precision and accuracy of fitted models, we fit multiple models on the same training dataset (using training datasets with nominal size of 40000 points). Repeated fits on the same training sample give nearly identical results, and the variance between fits on the same data is miniscule compared to the variance between training samples (Figure 9).Within each panel (a unique combination of training sample and validation sample), the multiple models produce nearly identical results (error and bias are constant across fits within a panel). This is strong evidence that for our purposes model fitting is functionally deterministic.

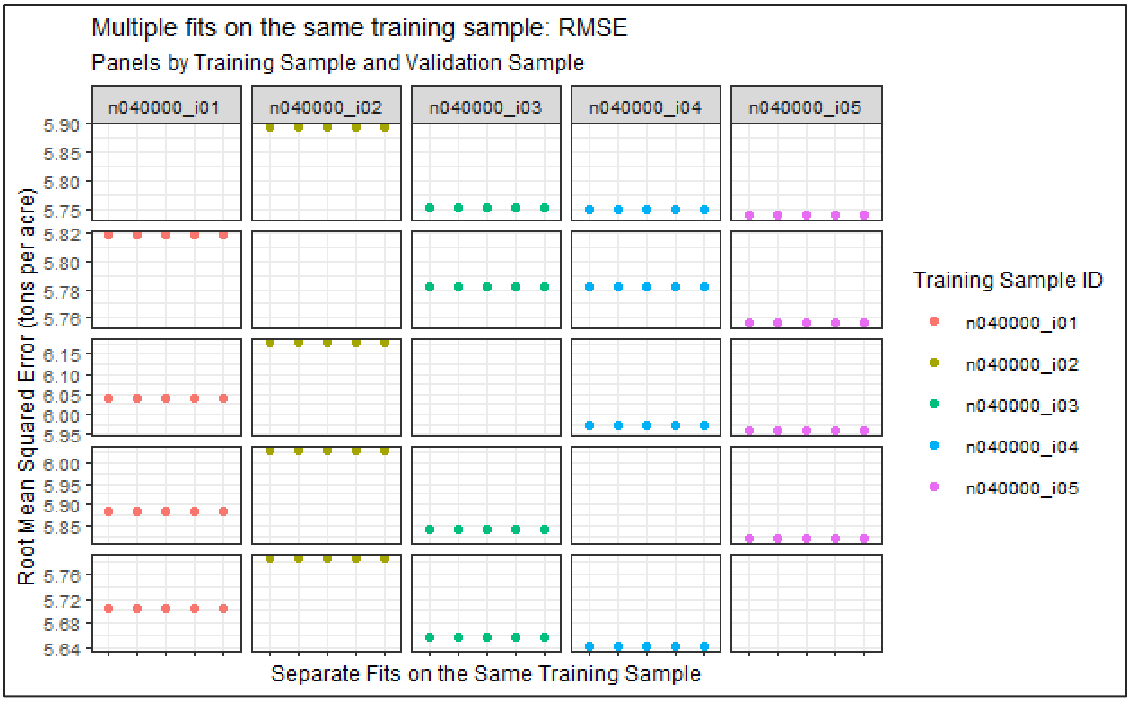

Figure 9: Comparing repeat model fits

Comparison of Predicted vs. Previous Fuels

The ultimate purpose of predicting interim FCCS maps is to provide fuel load estimates which are more precise and more accurate than the estimates provided by using out-of-date maps. By taking into account the previous FCCS category and intervening disturbances, multinomial models trained on at least 20,000 points consistently produce maps which predict current mapped fuels with greater precision and accuracy than a strategy of re-using the previous FCCS category (Figure 10 and Figure 11). Again, there appear to be diminishing returns on increasing the training sample size beyond 40000 locations points.

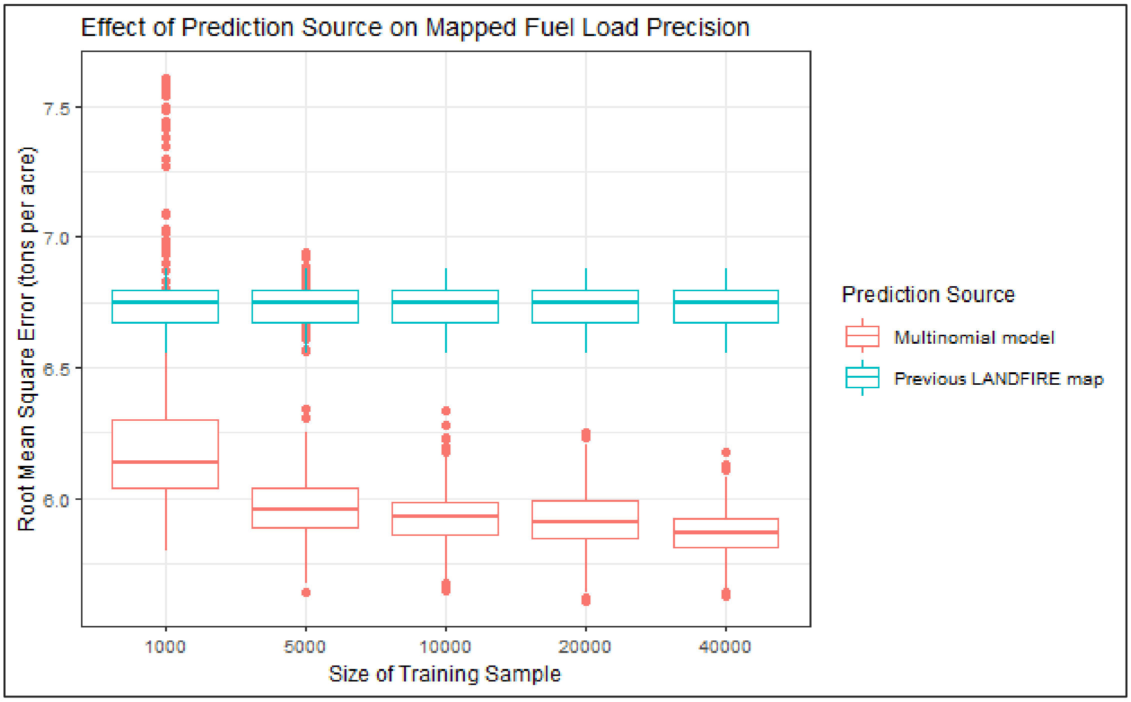

Figure 10: Precision of multinomial models

Figure 4 compares the precision (RMSE) of different multinomial models in predicting fuel loads for validation samples. The results are grouped by the size of the training sample used to fit the model, and source of fuel class predictions. "Previous LANDFIRE map" predictions assume that fuel classifications do not change over time, while the multinomial model accounts for disturbances. N = 1900 for the multinomial predictions, and N = 95 for the previous map predictions.

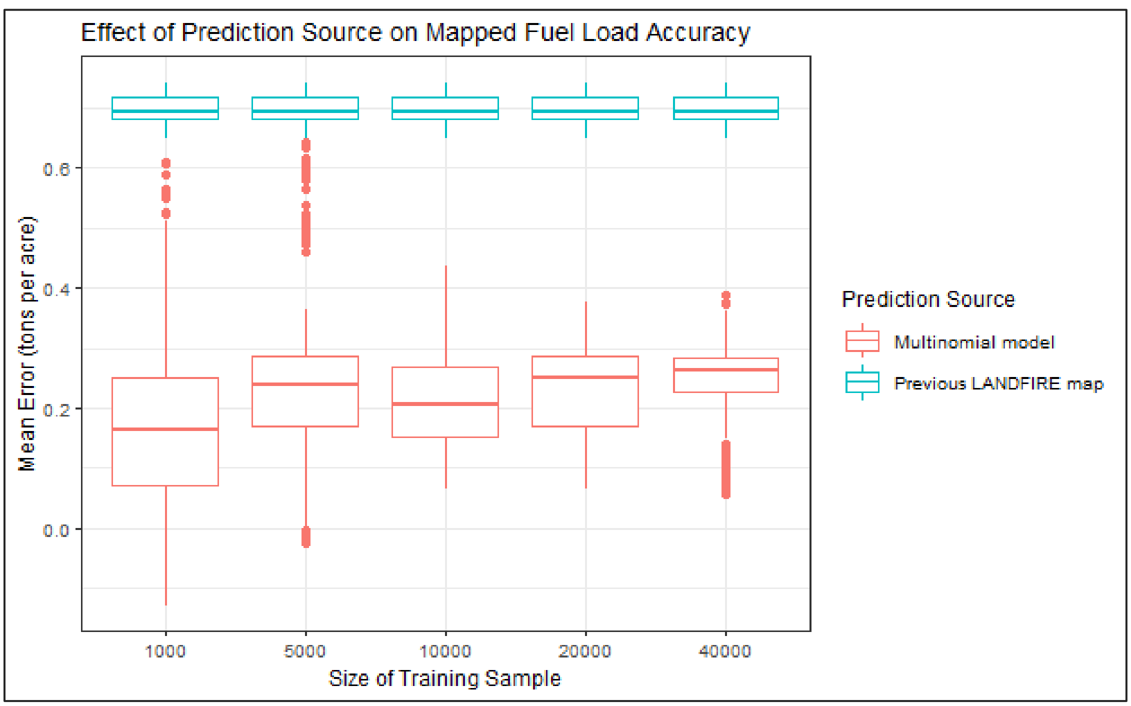

Figure 11: Accuracy of multinomial models

Figure 5 compares the accuracy (mean error) of different multinomial models in predicting fuel loads for validation samples. The results are grouped by the size of the training sample used to fit the model, and source of fuel class predictions. "Previous LANDFIRE map" predictions assume that fuel classifications do not change over time, while the multinomial model accounts for disturbances. N = 1900 for the multinomial predictions, and N = 95 for the previous map predictions.

Selecting a Training Sample

A single training sample of nominal size 40,000 locations (actual size 27,842) was selected to fit the multinomial model and predict fuels for statewide maps. The intended use for the predicted maps is to aggregate many pixels together and estimate emissions from an entire wildfire. In this context, minimizing bias is much more important than maximizing per-pixel precision. For this reason, we selected dataset *n040000_i20* to fit the model for statewide predictions: The model fit from dataset *n040000_i20* produced the most accurate (mean error closest to 0) predictions when applied to the other samples during validation testing (Figure 12).

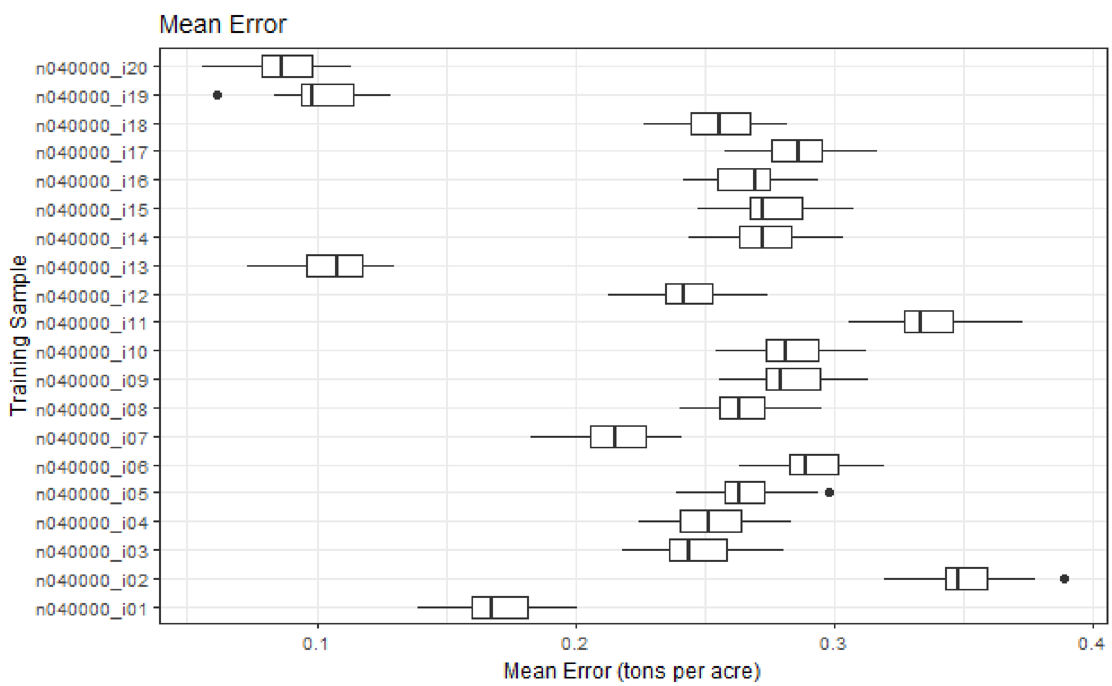

Figure 12: Mean Error of the Candidate Training Samples

Figure 6 shows the accuracy of each of the 20 candidate training samples when used to predict fuels for the 19 other samples (n = 380).