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Brattain Fire

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Ecological compression of vegetation information in wildfire spread prediction: a case study of the 2020 Brattain Fire

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Abstract

Background: Broad fuel categories simplify mapped vegetation, but it is unclear whether the distinctions removed help predict wildfire spread.

Aims: We tested whether vegetation composition improved prediction of the next observed fire-growth interval and examined the information lost by grouping fuel models.

Methods: For the 2020 Brattain Fire, we compared baseline predictors describing fire state, terrain, fuels, canopy and weather against the same predictors plus five vegetation fractions. We used chronological validation, logistic regression and Random Forest. A separate post hoc analysis compared native and grouped fuel codes.

Key results: Across 2754 held-out cell-interval observations, adding vegetation reduced logistic-regression log loss from 0.363889 to 0.363117 and Brier score from 0.107189 to 0.106988. Both 95% moving-block uncertainty intervals for the differences included zero, and benefits changed direction across evaluation periods. Grouping 27 fuel codes into five categories increased conditional entropy of detailed vegetation classes by 0.919 bits; retaining native codes did not consistently improve prediction.

Conclusions: Broad fuel groups discarded mapped vegetation distinctions without a demonstrated consistent predictive penalty in this single fire.

Implications: Testing additional fires and more direct measures of vegetation condition is needed before drawing broader conclusions about fire behavior.

Keywords: wildfire spread prediction; fire progression; vegetation composition; fire behavior fuel models; LANDFIRE; FEDS; ecological compression; fuel classification; chronological validation

Introduction

Weather, fuels, and topography influence how wildfires spread across a landscape. Their relative importance varies by region and fire environment. Holsinger et al. (2016) examined fire boundaries in four western U.S. study areas and found that weather and fuels were the strongest influences in the Northern Rockies, whereas fuels and topography were more important in the Southwest. They also found that recent burns, valley bottoms, and ridgetops were frequently associated with locations where fires stopped spreading.

Surface fuels are commonly represented using standardized fire behavior fuel models. The 40 models developed by Scott and Burgan (2005) describe fuel beds through properties such as loading, fuel type, and live and dead fuel components. LANDFIRE assigns these models using mapped vegetation type, cover, and height, among other inputs. Consequently, fuel-model maps already contain information derived from vegetation classifications. They are not independent of the EVT data examined here. Our baseline grouped the native FBFM40 codes into five categories: grass/grass-shrub, shrub, timber, slash/blowdown, and nonburnable. This grouping

discarded distinctions among fuel models within each category. Whether five additional EVT vegetation fractions improved prediction beyond these broad fuel groups was tested separately. Vegetation can influence fire behavior in ways that are not fully described by surface-fuel classifications. Loudermilk et al. (2022) described how vegetation structure affects local airflow, temperature, and moisture conditions, which in turn influence combustion and fire behavior. Empirical studies have also identified vegetation-related influences on fire progression. Across 314 wildfires in the southwestern United States, Harris et al. (2025) found that greater aspen cover was associated with lower daily area burned and slower linear spread. Holden et al. (2025) examined 196 fires in the northern Rocky Mountains and found that soil moisture and plant water stress improved predictions of daily fire growth compared with models using fuels and weather alone. These studies measured vegetation properties that differ from our predictors. Harris et al. (2025) examined aspen cover, which our broad tree fraction cannot distinguish from other tree communities. Holden et al. (2025) examined soil moisture and plant hydraulic stress, neither of which is directly measured by our pre-fire EVT fractions. Their findings provide reasons to investigate vegetation-related information, but they do not establish that adding our five vegetation fractions should improve predictions.

Previous wildfire modeling studies have tested how environmental inputs affect predictions. Huot et al. (2022) used feature-removal experiments in a next-day wildfire-spread model, finding that removing the previous fire location had a particularly large effect. Zou et al. (2023) modeled subsequent fire progression using satellite observations and environmental predictors. Taneja et al. (2021) examined a different aspect of input detail: they varied fuel-map resolution from 2 to 50 m in fire-spread simulations and found that coarser maps could obscure gaps in vegetation and change predicted fire extent. Our study concerns categorical rather than spatial

simplification. We tested whether five EVT fractions improved prediction when fire state, broad fuel categories, canopy, terrain, and weather were already included. In a separate post hoc analysis, we examined whether retaining native fuel-model categories instead of broad fuel groups improved held-out performance.

We investigated this question using the 2020 Brattain Fire in south-central Oregon. Our primary analysis compared a baseline model containing fire-state, terrain, surface-fuel, canopy, and weather predictors with an otherwise identical model that added five pre-fire LANDFIRE Existing Vegetation Type (EVT) fractions. These fractions described the proportions of tree, shrub, perennial herbaceous, annual herbaceous, and other vegetation within each 1-km cell. We tested whether these additional variables reduced prediction error for the next observed fire-growth interval using forward chronological validation. L2-regularized logistic regression was the primary model, with Random Forest used to examine whether the findings depended on model type.

We also conducted a post hoc analysis to examine the fuel classification itself. Using the detailed EVT classes, we measured how much mapped vegetation diversity was retained by native fuel-model codes compared with the five broad fuel categories. We then tested whether retaining native fuel codes improved prediction and whether adding EVT fractions produced different results under the two fuel representations. We use ecological compression to describe this reduction of mapped ecological detail into broader predictor categories. The analyses distinguish differences in the vegetation information represented by the predictors from differences in their measured predictive performance. Because the study concerns one fire and uses broad vegetation classifications, it cannot establish which vegetation characteristics caused differences in fire behavior or whether the findings extend to other landscapes.

109 **Materials and methods**

110 **Study area and fire-progression data**

111 We examined the 2020 Brattain Fire in south-central Oregon using observations from the Fire
112 Event Data Suite (FEDS) Western US Archive, version 1.0.0 (Orland et al. 2025). The study used
113 FEDS event 65371, generated with FireAtlas/FEDS v1.2.1. The archive does not provide an
114 official crosswalk between event identifiers and named incidents. We associated event 65371
115 with the Brattain Fire through its location, dates, progression, final area, and perimeter
116 correspondence. The FEDS tracking system groups 375-m VIIRS active-fire detections into fire
117 objects and derives successive fire perimeters and active fronts (Chen et al. 2022).

118 The Brattain Fire was used as a single-fire case study because its archived progression record
119 supported repeated observations of fire growth and could be paired with fuel, vegetation, terrain,
120 and weather data. The analyzed 1-km cells contained 27 native fuel-model codes and 87 detailed
121 vegetation classes, providing variation for comparing fuel classifications and vegetation
122 composition. The fire was not selected to represent the range of wildfire conditions in the
123 western United States.

124 We retained 16 fire-growth intervals between September 8 and 19, 2020, with durations ranging
125 from approximately 9.7 to 14.0 hours (median 12.3 hours). Fire progression was represented by
126 successive completed FEDS cumulative footprints. For each interval, we recorded whether the
127 center of an eligible, previously unburned grid cell was covered by the next observed cumulative
128 footprint. This outcome represents incorporation into the observed fire footprint, not exact
129 ignition time or flame arrival.

The primary analysis used 1-km cells in NAD27 / US National Atlas Equal Area (EPSG:9311). Cells already covered by the current cumulative footprint were excluded. Among the remaining cells, the primary candidate set included locations within 5 km of the current active front or within 2 km of the current cumulative perimeter. Eligibility was determined from the current fire state before the following observation was used to assign outcomes.

The resulting primary dataset contained 3,317 cell-interval observations across 642 unique cells, including 200 positive outcomes. A separate 2-km analysis contained 836 observations across 161 cells, including 49 positive outcomes. Figure 1 shows the study area and observed fire progression.

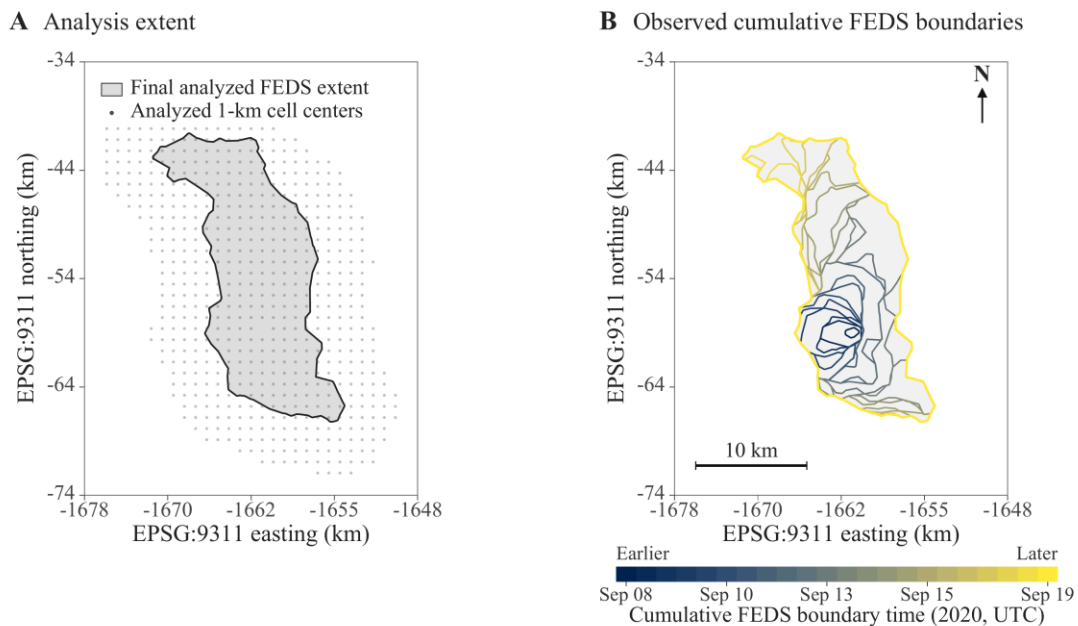


Fig. 1. Archived FEDS progression associated with the 2020 Brattain Fire. (A) Final analyzed extent and the 642 distinct 1-km analysis-cell centres. (B) Cumulative boundaries participating in retained intervals, September 8-19, 2020 (UTC). Colors use archived nominal state timestamps, not operational availability times. Geometries are retrospective observations, not model predictions; the association with Brattain is high-confidence inferred. Coordinates and the upward map direction use the EPSG:9311 grid.

Environmental predictors

The baseline model contained 24 raw predictor fields describing the current fire, terrain, surface fuel, canopy structure, and weather (Table 1). Four fire-state variables described distance to the active front, distance to the cumulative perimeter, membership in the four-level candidate-cell exposure classification, and log-transformed current cumulative fire area.

Five terrain variables described mean elevation, mean slope, source-to-target elevation difference, uphill alignment, and wind-slope alignment. Terrain data came from the USGS 3D Elevation Program (3DEP) one-third-arc-second digital elevation model (U.S. Geological Survey 2024).

Surface fuels were obtained from LANDFIRE 2016 Remap Fire Behavior Fuel Model data (LANDFIRE 2021). Native FBFM40 codes were grouped into five categories: grass/grass-shrub, shrub, timber, slash/blowdown, and nonburnable. Each predictor represented the proportion of the analysis cell assigned to that category.

Canopy predictors came from LANDFIRE canopy cover, canopy height, canopy base height, and canopy bulk density products. The baseline included the canopy-applicable fraction of each cell and four canopy measurements averaged over applicable areas.

Weather predictors were derived from archived High-Resolution Rapid Refresh (HRRR) forecasts (Dowell et al. 2022). They included mean eastward and northward 10-m wind components, maximum wind gust, mean 2-m temperature, and minimum 2-m relative humidity. Forecast initialization and archive availability were restricted to the relevant current-state cutoff.

The EVT-augmented model included the same 24 baseline fields and five additional LANDFIRE Existing Vegetation Type fractions: tree, shrub, perennial herbaceous, annual herbaceous, and other vegetation. LANDFIRE predictors represented mapped pre-fire conditions circa 2016.

Table 1. Predictor groups, definitions and data sources.

Group	Raw fields	Definitions	Sources and spatial support
Current fire state	4	Distances to active front and cumulative perimeter; hybrid risk membership; $\log(1 + t_0 \text{ hull area})$.	Completed-t0 FEDS geometry; distances at cell center.
Terrain	5	Mean elevation; mean physical slope; target-minus-source elevation; uphill alignment; wind-slope alignment.	3DEP one-third arc-second source; corrected 10-m working grid and physical East/North basis.
Fuel families	5	Full-cell fractions of grass/grass-shrub, shrub, timber, slash/blowdown and nonburnable fuel.	LF2016 FBFM40; 30-m native source pixel/cell intersection areas.
Canopy	5	Applicable fraction and conditional means of cover, height, base height and bulk density.	LF2016 CC/CH/CBH/CBD; 30 m; applicable-valid area-weighted means.
Weather	5	Mean earth-relative U10/V10; maximum gust; mean 2-m temperature; minimum 2-m RH.	HRRRv3 native 3-km forecasts; cell-center bilinear sampling and effective-interval summaries.
EVT augmentation	5 additional	Tree, shrub, perennial herbaceous, annual herbaceous and other cell-area fractions.	LF2016 EVT; 30 m; original EVT_SBCLS crosswalk, including disclosed graminoid limitation.

Baseline: 24 raw fields. Augmented: identical baseline plus five EVT fractions, 29 raw fields. Logistic design dimensions are 25 and 29 excluding intercept: three hybrid indicators (BOTH reference), nonburnable fuel reference omitted, and EVT other reference omitted only when augmented. Numerical fields use training-only population-SD scaling; exactly constant training coordinates map to zero. Canopy structural zeros apply only to nonapplicable rows. RF retains all fractions and four hybrid indicators: dimensions 27 and 32.

Spatial data processing

The analysis used globally anchored 1-km cells and nested 2-km cells in EPSG:9311, with the coordinate system's specified spherical Lambert azimuthal equal-area transformation.

LANDFIRE fuel, vegetation, and canopy rasters had a native 30-m resolution in EPSG:5070.

Source-pixel boundaries were densified, transformed into the analysis coordinate system, and

179 intersected with the analysis cells. Fuel and EVT fractions were calculated from the overlapping
180 area of each category divided by the full cell area. Source coverage and valid-data fractions were
181 tracked separately. The 2-km summaries combined four nested 1-km cells.

182 The USGS 3DEP elevation raster was bilinearly sampled onto a globally anchored 10-m working
183 grid with a 300-m surrounding buffer. Terrain gradients were calculated using the Horn method
184 and transformed from projected-grid coordinates into local eastward and northward components.
185 Cell elevation and physical slope were averaged across the working grid. Source-to-target
186 elevation difference was calculated as target-cell mean elevation minus source-point elevation.
187 Uphill and wind-slope alignments were calculated using normalized vector relationships in the
188 same physical coordinate basis.

189 Canopy measurements were averaged over valid, canopy-applicable portions of each cell.
190 Nonapplicable canopy values remained missing in the raw feature tables and received predefined
191 structural-zero values during model preprocessing. HRRR forecasts were bilinearly sampled at
192 cell centers and summarized over the relevant observation intervals.

193 Fire-state predictors and candidate-cell eligibility were calculated from completed-current-state
194 FEDS geometry. Outcomes were determined from the following observed fire state. The
195 evaluation was retrospective: although predictor construction was restricted to current-state
196 information and cutoff-valid weather forecasts, the original processing availability and complete
197 pre-merge event lineage of the FEDS archive could not be reconstructed independently.

198 Before finalizing the reported analyses, we corrected errors in an earlier environmental feature-
199 extraction implementation. These affected handling of the EPSG:9311 coordinate transformation,
200 area-based aggregation of categorical raster data, and terrain-gradient calculations. The

corrections required regeneration of affected environmental predictors and recomputation of the reported primary and sensitivity analyses. The post hoc fuel-classification analyses also used the corrected features. Earlier numerical results are superseded; the correction history and corrected outputs are documented in the associated research compendium.

Model fitting and chronological validation

L2-regularized logistic regression was the primary model, with Random Forest used as a nonlinear robustness check. Logistic regression was fitted using the L-BFGS solver, an intercept, and no class weighting. Regularization strength was selected from $C = 0.1$ and $C = 1.0$ using chronological tuning restricted to each available training history.

Numerical preprocessing used means and population standard deviations calculated exclusively from the training observations. Predictors with zero training variance were assigned fixed-zero transformed values. Fuel and EVT compositions used fixed reference categories, and categorical exposure indicators were encoded separately. After encoding, logistic-regression design matrices contained 25 baseline or 29 augmented predictor columns, excluding the intercept.

Random Forest models used 1,000 trees, a maximum depth of six, log-loss splitting, bootstrap sampling, and the square root of the available predictor count at each split. Minimum leaf fractions of 0.02 and 0.05 were compared during tuning. Final predictions were averaged across five fitted seeds.

The retained fire-growth intervals were divided chronologically into four blocks: B1 (1, 3, 4, 5), B2 (6, 8, 9, 10), B3 (11, 12, 14, 15), and B4 (16, 18, 21, 22). Models trained on B1 were evaluated on B2; models trained on B1–B2 were evaluated on B3; and models trained on B1–B3 were evaluated on B4. Preprocessing and hyperparameter tuning used only observations

available within each training history. Baseline and EVT-augmented models were evaluated on identical held-out observations.

Model fitting and evaluation used Python 3.12.13 with scikit-learn 1.9.0, NumPy 2.5.1, and SciPy 1.18.0. Geospatial processing used Rasterio 1.5.0, GDAL 3.12.4, pyproj 3.7.2, and PROJ 9.7.1.

Performance evaluation and uncertainty

We evaluated predicted probabilities using log loss and Brier score. Both metrics decrease with better probabilistic predictions. Paired differences were calculated as baseline loss minus EVT-augmented loss, so positive values indicate an improvement after adding EVT.

Losses were first averaged within each held-out interval, then equally across the four intervals in each evaluation block and across the three held-out blocks. The primary held-out evaluation contained 2,754 cell-interval observations, including 172 positive outcomes across 610 distinct cells. Sample sizes for each chronological evaluation block are reported in Supplementary Table S1.

Uncertainty in paired loss differences was summarized using 10,000 moving-block bootstrap replicates over the 12 ordered held-out intervals. The primary bootstrap used blocks of two consecutive intervals; blocks of three were examined as a sensitivity check. We report percentile-based 95% intervals as descriptive measures of within-fire uncertainty. We calculated average precision and the area under the receiver operating characteristic curve (ROC-AUC) separately for each held-out interval. Probability calibration was examined using separate calibration-intercept and calibration-slope fits and five approximately equal-count reliability groups within

each interval. Calibration fits that did not produce valid estimates were recorded as undefined.

These diagnostics did not alter the predicted probabilities.

Sensitivity analyses

We repeated the logistic-regression comparison at 2-km resolution and excluded the two earliest training intervals in a separate analysis. Three alternative candidate-cell definitions were also evaluated: locations within 5 km of the active front, within 2 km of the cumulative perimeter, or within 5 km of the cumulative perimeter.

Two additional analyses restricted observations using 500-m and 1,000-m boundary exclusions. These were sensitivity restrictions rather than predictors available for operational forecasting. We also recalculated the primary paired loss differences after omitting each held-out interval in turn, without refitting models.

Exploratory analysis of fuel classification

We conducted a separate post hoc analysis of fuel classification. We compared how much variation in detailed EVT classes remained within native FBFM40 fuel codes and within the five broader fuel categories. Area-weighted conditional entropy was calculated using 642 unique 1-km cells.

Four additional logistic model specifications were evaluated using the same corrected fire-state, terrain, canopy, and weather predictors: broad fuel fractions, broad fuel fractions with EVT, native fuel-code fractions, and native fuel-code fractions with EVT.

These exploratory models used fixed orthonormal contrasts for compositional predictors, with regularization independently selected under the original chronological validation structure.

Because they differed in predictor dimensions and preprocessing from the primary comparison, their results were treated as exploratory rather than replacements for the original analysis.

Results

Primary 1-km analysis

The primary held-out evaluation included 2,754 cell-interval observations from 610 distinct cells across 12 fire-growth intervals. Of these observations, 172 were positive next-interval incorporations.

Adding five EVT fractions to the baseline logistic-regression model reduced mean log loss from 0.363889 to 0.363117, a difference of 0.000772 (Table 2). Brier score decreased from 0.107189 to 0.106988, a difference of 0.000201. Both differences were small. The 95% moving-block bootstrap intervals included zero for both metrics: -0.003466 to 0.007011 for log loss and -0.001085 to 0.002144 for Brier score using blocks of two intervals. Results using blocks of three intervals were similar.

Across the 12 held-out intervals, ROC-AUC ranged from 0.850 to 0.974 for the baseline logistic model and from 0.853 to 0.974 after EVT augmentation. Average precision ranged from 0.143 to 0.795 and from 0.136 to 0.798, respectively. These values are ranges of interval-specific scores, not pooled performance estimates.

The reliability analysis showed substantial differences between predicted probabilities and observed incorporation frequencies in some intervals. During interval 8, the highest-probability group of 31 baseline observations had a mean predicted probability of 0.059, compared with an observed incorporation fraction of 0.581. During interval 12, the corresponding values were 0.967 and 0.295 among 44 observations. The EVT-augmented model showed similar

discrepancies. These results indicate that relatively strong discrimination did not consistently translate into well-calibrated probabilities.

The direction of the difference varied across evaluation periods (Fig. 2). During B2, the EVT-augmented model performed slightly worse than the baseline, with differences of -0.000090 in log loss and -0.000143 in Brier score. EVT augmentation performed better during B3, with corresponding differences of 0.008424 and 0.002673 . During B4, both differences became negative again, at -0.006018 and -0.001926 . The positive overall mean therefore reflected the improvement during B3 rather than a consistent advantage across the fire's progression.

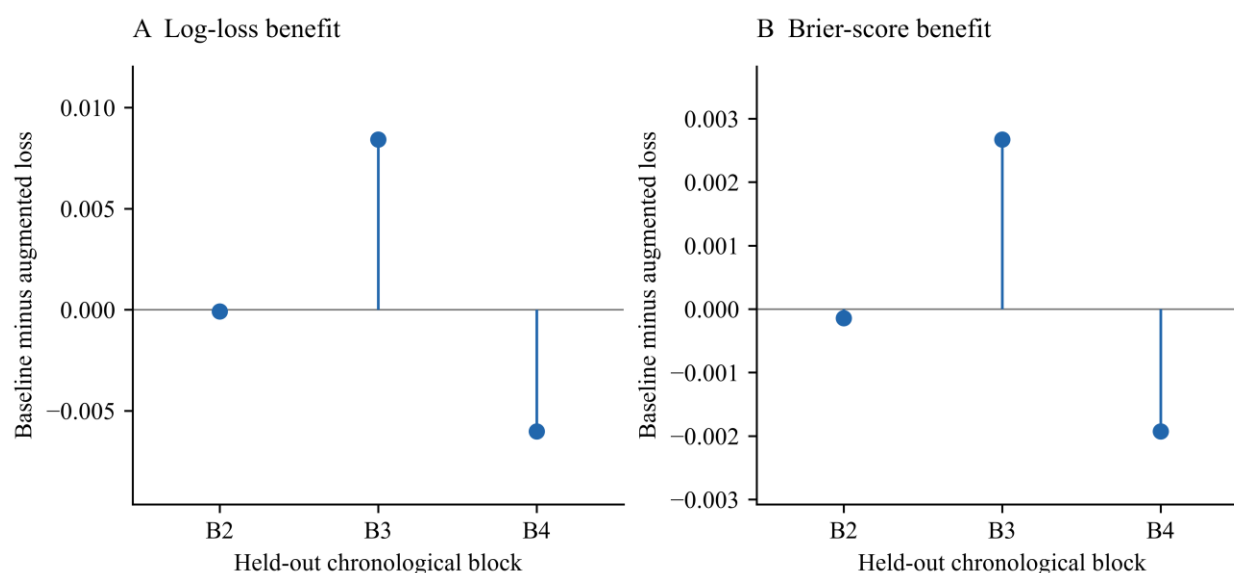


Fig. 2. Differences in held-out log loss (A) and Brier score (B) between baseline and EVT-augmented logistic-regression models across chronological evaluation blocks B2–B4. Each point represents the mean paired difference across four intervals within a block. Positive values favor EVT augmentation. Vertical stems connect each estimate to zero and do not represent uncertainty intervals.

Model and spatial-resolution comparisons

The Random Forest comparison produced a small reduction in log loss after adding EVT fractions, from 0.214158 to 0.212091 . The 95% interval for the difference crossed zero with a bootstrap block length of two but was slightly positive with a length of three. Brier score

increased from 0.053668 to 0.053707, indicating slightly worse performance after augmentation. Its uncertainty intervals included zero under both block lengths. At 2-km resolution, the logistic-regression results favored the baseline model. Adding EVT increased log loss from 0.226178 to 0.227436 and Brier score from 0.069582 to 0.069767. Both paired differences had uncertainty intervals that included zero (Table 2).

Table 2. Predictive performance of baseline and EVT-augmented models in the primary and robustness analyses.

Analysis	Metric	Baseline	Baseline + EVT	Benefit	95% interval L=2	95% interval L=3
Primary 1-km logistic	Log loss	0.363889	0.363117	0.000772	[-0.003466, 0.007011]	[-0.002833, 0.007840]
Primary 1-km logistic	Brier	0.107189	0.106988	0.000201	[-0.001085, 0.002144]	[-0.000902, 0.002321]
Random Forest robustness	Log loss	0.214158	0.212091	0.002068	[-0.000227, 0.005889]	[0.000073, 0.005902]
Random Forest robustness	Brier	0.053668	0.053707	-0.000039	[-0.000319, 0.000259]	[-0.000314, 0.000225]
2-km logistic	Log loss	0.226178	0.227436	-0.001258	[-0.004167, 0.001479]	[-0.004343, 0.001274]
2-km logistic	Brier	0.069582	0.069767	-0.000186	[-0.000994, 0.000734]	[-0.000955, 0.000601]

Benefit = baseline loss minus EVT-augmented loss. Positive favors EVT augmentation. Scores average observations within intervals, then intervals within blocks, then blocks equally. Descriptive moving-block percentile intervals use lengths 2 and 3, 10,000 replicates and seed 20200908. RF averages five seed probabilities before scoring.

Sensitivity analyses

Removing the two earliest training intervals produced small positive differences after EVT augmentation: 0.001338 for log loss and 0.000192 for Brier score. Both uncertainty intervals included zero (Table 3).

Results also differed according to the candidate-cell definition. Restricting candidates to within 5 km of the active front slightly favored the baseline model, whereas a 5-km cumulative-perimeter risk set produced small improvements with EVT. Under the 2-km cumulative-perimeter risk set,

adding EVT increased log loss from 0.413284 to 0.583511. This large difference was associated with extreme predictor extrapolation in the augmented B2 model, including an annual-herbaceous EVT value more than 256 training standard deviations from its training mean and two saturated predicted probabilities. The result was retained, but it does not establish a vegetation-related cause for the deterioration.

The 500-m boundary-exclusion analysis slightly favored the baseline model, with differences of -0.001285 in log loss and -0.000447 in Brier score. With a 1,000-m exclusion, the initial training block retained 452 observations but no positive outcomes. The B1-to-B2 models therefore could not be fitted, and the prespecified three-block aggregate was not estimable.

In the leave-one-interval-out diagnostic, removing individual evaluation intervals sometimes changed the sign of the aggregate result. The recalculated log-loss differences ranged from -0.000119 to 0.003037 , and Brier-score differences ranged from -0.000108 to 0.000961 . The small positive overall result was therefore sensitive to which held-out intervals were included. Results for each omitted interval are provided in Supplementary Table S6.

Table 3. Predictive performance under alternative training histories, candidate-cell definitions and boundary exclusions.

Analysis	Metric	Baseline	Baseline + EVT	Benefit	95% interval L=2	95% interval L=3
No early history	Log loss	0.422130	0.420792	0.001338	[-0.004199, 0.009752]	[-0.003486, 0.010693]
No early history	Brier	0.122792	0.122600	0.000192	[-0.001284, 0.002465]	[-0.001128, 0.002622]
Active front within 5 km	Log loss	0.451506	0.452491	-0.000984	[-0.007233, 0.007501]	[-0.006621, 0.008234]
Active front within 5 km	Brier	0.134467	0.134830	-0.000364	[-0.002283, 0.002329]	[-0.002135, 0.002464]
Perimeter within 2 km	Log loss	0.413284	0.583511	-0.170227	[-0.542754, 0.032520]	[-0.541655, 0.029828]
Perimeter within 2 km	Brier	0.128086	0.137406	-0.009320	[-0.037623, 0.009980]	[-0.037110, 0.009178]
Perimeter within 5 km	Log loss	0.261299	0.260037	0.001262	[-0.001583, 0.005857]	[-0.001335, 0.006487]
Perimeter within 5 km	Brier	0.076958	0.076606	0.000352	[-0.000498, 0.001763]	[-0.000437, 0.001897]
Boundary exclusion 1000 m	Log loss	NE	NE	NE	NE	NE
Boundary exclusion 1000 m	Brier	NE	NE	NE	NE	NE
Boundary exclusion 500 m	Log loss	0.232731	0.234016	-0.001285	[-0.006487, 0.005486]	[-0.005731, 0.006091]
Boundary exclusion 500 m	Brier	0.062929	0.063376	-0.000447	[-0.002048, 0.001528]	[-0.001914, 0.001707]

Benefit = baseline loss minus EVT-augmented loss. Positive favors EVT augmentation. Scores average observations within intervals, then intervals within blocks, then blocks equally. Descriptive moving-block percentile intervals use lengths 2 and 3, 10,000 replicates and seed 20200908. RF averages five seed probabilities before scoring.

NE = not estimable; the full three-block comparison could not be calculated because the initial training block contained no positive outcomes. Boundary exclusion 1000 m: both B1-to-B2 roles are nonestimable: 452 training observations, zero positives. Available baseline to EVT scores: B3 log loss 0.080527 to 0.079605, Brier 0.014623 to 0.014487; B4 log loss 0.046136 to 0.047538, Brier 0.010245 to 0.010652. The full three-block aggregate and uncertainty are NOT ESTIMABLE; no two-block substitute. Boundary exclusions use t0/t1 boundary distances as a restricted sensitivity, not as t0 predictors.

Perimeter-within-2-km augmented B2 has two saturated probabilities and an EVT coordinate up to 256.342 training SDs; the unfavorable loss is retained. Primary logistic predictions have no saturated probabilities. Computation passing does not remove extrapolation concerns.

Exploratory analysis of fuel classifications and vegetation composition

The 642 analyzed 1-km cells contained 27 observed native FBFM40 fuel-model codes and 87 detailed EVT classes. In the post hoc analysis, the conditional entropy of detailed EVT classes was 2.348 bits when conditioned on native fuel codes and 3.267 bits when conditioned on the five broad fuel categories. The difference of 0.919 bits indicates that the broader fuel classification retained fewer distinctions among detailed EVT classes (Supplementary Table S3).

Retaining native fuel-model fractions did not consistently improve prediction. In the exploratory logistic models, mean log loss was 0.364791 with broad fuel categories and 0.365195 with native fuel categories. After adding EVT fractions, the corresponding scores were 0.364601 and 0.364919 (Supplementary Table S2).

The log-loss improvement from adding EVT was 0.000190 with broad fuel categories and 0.000276 with native fuel categories. The difference between those improvements was -0.000085 . All reported moving-block bootstrap intervals for the exploratory comparisons included zero (Supplementary Table S4). Block-level results for the four exploratory models are provided in Supplementary Table S5.

These exploratory results show that the broader fuel categories discarded measurable distinctions among mapped vegetation classes. However, retaining native fuel categories or adding the five EVT fractions did not produce a consistent improvement in the models' held-out predictions.

Discussion

Across the 642 analyzed cells, the area-weighted conditional entropy of 87 detailed EVT classes was 2.348 bits when conditioned on native fuel-model codes and 3.267 bits when conditioned on the five broader fuel categories. The 0.919-bit difference quantifies how much additional

uncertainty about mapped vegetation classes remained after grouping the fuel codes. Because each broad fuel category is derived from its native codes, increased conditional entropy is an expected consequence of grouping; the measured difference describes its magnitude in this landscape. The predictive models, however, did not use the 87 detailed EVT classes. They used five broad vegetation fractions, which could not distinguish individual communities within each fraction. The entropy difference therefore measures the loss of mapped categorical detail, not a demonstrated loss of information useful for predicting wildfire spread.

In the primary 1-km logistic-regression analysis, adding five EVT fractions reduced mean log loss by 0.000772 and Brier score by 0.000201. Both improvements were small, and the moving-block uncertainty intervals included zero. The direction of the log-loss difference also changed across evaluation blocks. Adding EVT produced a small deterioration during B2, an improvement during B3, and a larger deterioration during B4. Although the overall average favored EVT, the improvement was concentrated in B3 rather than repeated throughout the evaluation period.

The leave-one-interval-out analysis showed further instability. Omitting individual intervals produced log-loss differences ranging from -0.000119 to 0.003037 and Brier-score differences from -0.000108 to 0.000961 . Removing interval 16 or 21 reversed the overall log-loss difference, while removing interval 11, 16, or 21 reversed the Brier-score difference. These results indicate that the small positive aggregate finding depended partly on which observation periods were included.

The results also differed across model types and spatial resolutions. Random Forest produced a small improvement in log loss but a slight deterioration in Brier score after EVT augmentation. At 2-km resolution, both metrics slightly favored the baseline model. These differences do not

establish that either model type or spatial resolution is generally better suited to vegetation data. They show that the incremental value of the five EVT fractions was not consistent across the tested configurations.

The reliability analysis also limits the interpretation of the models' predicted probabilities. Although ROC-AUC was relatively high in several intervals, some reliability groups showed large differences between predicted and observed incorporation frequencies. Neither predictor set consistently resolved these discrepancies. The models should therefore be interpreted as retrospective comparisons of environmental information, not as calibrated operational fire-spread forecasts.

Fuel classifications and vegetation maps describe related but different properties of a landscape. The Scott and Burgan (2005) fire behavior fuel models characterize fuel beds using properties relevant to surface fire spread, including loading, fuel structure, and live and dead material. LANDFIRE EVT describes mapped vegetation types. Two locations with the same broad fuel category may therefore contain different vegetation communities without necessarily having different fuel properties or fire behavior.

There are several possible explanations for the small and inconsistent changes after EVT augmentation. First, LANDFIRE fuel models are assigned partly from vegetation type, cover, and height. Some information in the EVT fractions may therefore overlap with the existing fuel and canopy predictors. Second, the five vegetation fractions may be too broad to represent properties that influence combustion. The tree fraction, for example, does not distinguish aspen from other tree communities, although Harris et al. (2025) found differences in fire spread associated with aspen cover. Likewise, Holden et al. (2025) identified soil moisture and plant hydraulic stress as important predictors of daily fire growth, but neither was directly measured

by our pre-fire EVT fractions. We cannot determine whether overlapping predictors, insufficient vegetation detail, limited training data, or unmeasured environmental conditions explain the weak and inconsistent improvements in this case.

The post hoc comparisons tested whether retaining native fuel-model codes changed predictive performance. Mean held-out log loss was 0.364791 with the five broad fuel categories and 0.365195 with native fuel-code fractions. Adding EVT reduced log loss by 0.000190 with broad fuel categories and by 0.000276 with native codes; both differences had descriptive uncertainty intervals that included zero (Supplementary Tables S2 and S4). These results do not establish that the two fuel representations are predictively equivalent. The native-code models contained more predictors than the broad-fuel models (65 versus 25 without EVT), and model performance also depended on regularization. The comparisons therefore cannot isolate the effect of categorical grouping from differences in model dimension and fitting. Nor do they establish that the fuel distinctions removed through grouping are unimportant to fire behavior.

The sensitivity analyses indicate that the choice of candidate locations can affect the measured contribution of vegetation variables. Most alternate candidate-cell definitions produced small and uncertain differences between the models. The 2-km perimeter-only risk set produced a much larger deterioration after EVT augmentation. However, that result was associated with extreme extrapolation of an annual-herbaceous predictor and saturated probabilities in one evaluation block. It should not be interpreted as evidence that annual herbaceous vegetation caused poorer fire predictions. The boundary-exclusion analyses also illustrate how changes in the evaluation sample can affect model estimation; the 1,000-m exclusion left no positive outcomes in the initial training block, preventing the full comparison.

Several limitations restrict the ecological interpretation of these results. The analysis concerned one wildfire and only 12 held-out growth intervals. Many cells appeared repeatedly across intervals, so the 2,754 held-out observations were not independent spatial replicates. Fuel and EVT maps represented pre-fire conditions and did not capture changing fuel moisture, vegetation condition, or suppression activity during the fire. The original EVT crosswalk also had limitations in its treatment of perennial graminoid vegetation. Furthermore, the outcome represented incorporation into successive satellite-derived cumulative fire footprints rather than direct observation of flame movement. Although current-state predictors and weather inputs were restricted chronologically, the retrospective FEDS archive's complete event-processing lineage could not be verified.

For similar retrospective prediction studies, these findings support testing the contribution of additional vegetation layers rather than assuming that greater categorical detail will improve predictions. During the Brattain Fire, adding five EVT fractions produced no consistent improvement in held-out log loss or Brier score, and some evaluation intervals showed substantial probability miscalibration. The results do not justify removing vegetation information from existing fire-behavior models or selecting coarser fuel maps for operational predictions. They apply to one fire, the environmental variables tested here, and a response based on satellite-observed incorporation into successive fire footprints. Comparisons across additional fires, with measurements of fuel moisture, vegetation structure, and composition, would be needed to determine when greater ecological detail helps predict spread.

Conclusions

This study examined whether five pre-fire vegetation fractions improved prediction of previously unburned 1-km cells being incorporated into the next satellite-derived cumulative fire footprint during the 2020 Brattain Fire. Grouping native LANDFIRE fuel-model codes into five broad categories reduced the distinctions among mapped vegetation types, as measured by a 0.919-bit difference in conditional entropy. However, retaining more detailed fuel classifications did not consistently improve predictive performance.

In the primary 1-km logistic-regression analysis, adding five EVT fractions reduced held-out log loss by 0.000772 and Brier score by 0.000201. Both improvements were small, varied across evaluation periods, and had 95% moving-block bootstrap intervals that included zero. The exploratory comparisons using native fuel-model codes also showed no consistent predictive advantage.

In this case, broad fuel categories retained less information about detailed vegetation classes, but the richer predictor representations tested here did not produce a consistent predictive advantage. They do not establish that the discarded differences are irrelevant to fire behavior. Further research across multiple fires, including more direct measurements of vegetation and fuel conditions, is needed to determine when additional ecological information improves wildfire-spread prediction.

Data availability

Corrected derived data, selected analysis results, source code, provenance records, publication tables and figures supporting this study are available in the corrected research compendium (Ko and Ko 2026), Zenodo, <https://doi.org/10.5281/zenodo.23551981>. Version 1.0.0 contains

superseded numerical findings. The correction history and reproduction limitations are documented in the compendium. Raw FEDS, LANDFIRE, USGS 3DEP and HRRR source datasets are not redistributed and must be obtained from their respective providers.

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Author contributions

Christopher Ko and Hannah Ko contributed to the conceptualization of the study. Christopher Ko curated the data, developed the methodology and software, performed the formal analyses, validated the results, and prepared Figures 1–2 and Tables 1–3. Christopher Ko led the manuscript drafting, and Hannah Ko contributed to data collection and manuscript writing. Hannah Ko also contributed to the scientific interpretation of the study and substantive revision of the manuscript. Both authors reviewed and edited the manuscript and approved the final version.

Ethics approval and consent to participate

Not applicable. This study did not involve human participants or animals.

Consent for publication

Not applicable.

503 **Competing interests**

504 The authors declare that they have no competing interests.

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553

554 **Supplementary methods**

555 Ecological compression of vegetation information in wildfire spread prediction: a case study of
556 the 2020 Brattain Fire

557 Christopher Ko and Hannah Ko

558 **Analysis geometry and extraction.** We retained globally anchored 1-km EPSG:9311 cells and
559 nested 2-km cells. Coordinate transformations preserved spherical Lambert azimuthal equal-area
560 semantics (+R_A; origin 45 degrees N, 100 degrees W; Clarke 1866), using recorded offline
561 datum operations and explicit geographic-axis conventions. The saved EPSG:5070 operation
562 inverts GRS80 Albers, applies the recorded (+8,-159,-175 m) geocentric translation and
563 projects to spherical LAEA; the geographic EPSG:4269 operation explicitly swaps native
564 latitude/longitude axes. These particular offline operations were validated, not claimed to be
565 equivalent to every alternative datum grid. Densified native 30-m LF2016 pixel footprints were
566 transformed and intersected with fixed analysis cells. Fuel-family and EVT indicator areas were
567 divided by full cell area; covered, valid and applicable areas were tracked separately, and integer
568 class codes were never averaged. Two-kilometer fractions pooled four nested children. The
569 corrected selected universe contains 688 unique 1-km children and 167 parents, including
570 642/161 primary cells.

571 **Terrain.** USGS 3DEP one-third-arc-second elevations were bilinearly sampled at globally
572 anchored 10-m working-pixel centers with a 300-m halo. Positive-grid-east/positive-grid-north
573 Horn derivatives were converted to local physical East/North gradients using $g_{EN} = J^T$
574 g_{grid} , where $J = d(grid\ x,y)/d(local\ physical\ East,North)$ uses Clarke-1866 ellipsoidal distance
575 conventions. Physical slope was $atan(||g_{EN}||)$, in degrees, averaged across working pixels; it
576 was not the slope of the cell-mean gradient. Target elevation was the mean of working-pixel
577 elevations; source elevation used the containing 10-m pixel at the nearest completed-t0 front
578 point, or hull-boundary point for perimeter-backstop-only cells. Target-minus-source elevation
579 and normalized uphill/wind-slope dot products used the corrected common physical basis. The
580 straight source-to-target grid displacement was transformed with inverse J at the target; it was
581 not replaced by a geodesic trajectory. Degenerate gradient, wind or displacement norms $\leq 1e-6$
582 gave alignment zero. Earth-relative HRRR winds were not rotated twice or reversed to a
583 meteorological-from direction.

584 **Canopy and vegetation.** Canopy applicability was valid canopy cover >0 . Cover retained
585 percent units; canopy height/base-height codes were divided by 10 and bulk-density codes by
586 100. Conditional means used applicable-valid area denominators, pooling
587 numerator/denominator across children at 2 km. Raw values were missing where canopy was
588 nonapplicable; only those structural states became zero during model preprocessing. Applicable
589 nonfinite values rejected. Fuel groups were GR+GS, SH, TU+TL, SB and NB. The original
590 EVT_SBCLS label crosswalk defined five cell-area fractions: tree, shrub, perennial herbaceous,
591 annual herbaceous and other. The unchanged string-matching limitation described below means

these are implemented broad groups, not exhaustive botanical classifications or detailed community indicators.

Weather and observation time. Effective t_0 was the latest VIIRS observation incorporated in the completed current FEDS state, not its nominal 00:00/12:00 bin label. The latest eligible HRRRv3 initialization and its complete required forecast-object set had to be archived by that cutoff; the preserved weather QC records 226 objects across 16 retained intervals. Future forecast-valid times were permitted only from those already available forecasts; later cycles and realized future weather were excluded from primary predictors. Native HRRR cell-center bilinear samples supplied endpoint-interpolated trapezoidal means of earth-relative 10-m U/V and 2-m temperature, maximum gust and minimum 2-m relative humidity over the effective interval; temperature converted from Kelvin to Celsius. Native grid-relative winds were rotated once to earth-relative coordinates.

Fire states and limitations. Eligibility was fixed from completed- t_0 geometry: centers outside the current cumulative hull and within 5 km of its active front or 2 km of its hull boundary. The binary response was center incorporation by the next completed FEDS state. Retained horizons were 9.7-14.0 hours (median 12.3), not exact 12-hour operational forecasts. FEDS Western-US v1.2.1 event fireID/mergeid 65371 was associated with Brattain by high-confidence inference. Its retrospective postprocessing, unrecovered original pre-merge lineage, imperfect perimeter reconstruction and historical publication latency prevent a claim that every state would have existed operationally at the observation cutoff, or that all upstream lineage look-ahead was independently excluded. The study remains conditional, single-fire and noncausal; suppression is an unresolved major limitation. Boundary-exclusion sensitivities use t_0/t_1 boundary distances for evaluation/QC restrictions, not as primary t_0 predictors.

Models and preprocessing. The primary comparison used the identical 24-field conventional baseline with or without the five EVT fractions. Logistic designs had 25/29 columns excluding the intercept, using nonburnable fuel, EVT other and hybrid BOTH as references. Numeric predictors were centered/scaled by the exact current training history using population SD; exactly zero-SD coordinates were fixed to zero, without imposing an unrecorded near-zero threshold. Inner-validation preprocessing was fitted on inner training only; the final refit used the full outer training history only. Frame/key correspondence and paired held-out support were preserved. L2 logistic regression used lbfgs, an intercept, no class weighting, maximum 5000 iterations and tolerance $1e-8$. Candidates $C=0.1/1$ were selected by the frozen chronological inner mean-interval log-loss procedure, with ties within $1e-12$ favoring $C=0.1$; all six primary role/evaluation fits selected $C=0.1$. Fixed/inherited sensitivity policies were unchanged and inheritance used corrected parents only. RF robustness retained all fuel/EVT fractions and four hybrid indicators (27/32 columns), 1000 trees, log-loss splits, depth 6, sqrt feature sampling, bootstrap sampling, `min_samples_split=2` and the original leaf-fraction candidates 0.02/0.05. It averaged probabilities from final seeds 20200908-20200912 before scoring; this is not an average of five seed-specific metrics.

Validation, metrics and uncertainty. B1 intervals 1/3/4/5 trained B2 intervals 6/8/9/10; B1+B2 trained B3 intervals 11/12/14/15; B1+B2+B3 trained B4 intervals 16/18/21/22. B2 inner splits were (1,3)->4 and (1,3,4)->5; B3 used B1->B2; B4 used B1->B2 and B1+B2->B3. Candidate scores averaged intervals within each split then splits equally. Losses were averaged across observations within each interval, four intervals within each block and three blocks equally, without pooling all held-out observations. AP and ROC-AUC were calculated separately for each interval with both classes, using sklearn `average_precision_score` and `roc_auc_score`; AP is not a trapezoidal PR-AUC. Paired benefit was baseline minus augmented loss. Moving-block percentile intervals used the 12 ordered interval differences, all overlapping noncircular blocks of length 2 or 3, independent uniform sampling of contiguous blocks with replacement, concatenation/truncation to length 12, 10000 replicates, seed 20200908 and the 2.5/97.5 percentiles (NumPy default linear quantiles). They are descriptive within-fire intervals, not independent-cell significance tests. LOIO was no-refit. The two 1000-m boundary B1 tasks remained nonestimable; no two-block replacement for the missing three-block aggregate was permitted.

Calibration diagnostics. On each held-out interval, predicted logits were clipped to probabilities [1e-15, 1-1e-15]. An offset-only logistic optimization estimated calibration-in-the-large with slope fixed at 1; a separate intercept-plus-logit optimization supplied the calibration slope. Thus the two reported scalars are not the intercept/slope of one jointly fitted calibration equation. SciPy BFGS used tolerance 1e-10 and maximum 10000 iterations, and unsuccessful optimization returned NOT_DEFINED. These diagnostics did not recalibrate saved predictions. Five approximately equal-count reliability bins were formed separately within each interval by stable sorting on probability, interval and cell ID and `array_split`; saved counts, mean probabilities and event fractions are descriptive, not common fixed probability bins or independent-location samples.

657 ***Supplementary table S1 Evaluation support***

Analysis	B2 train/test/positive/cells	B3 train/test/positive/cells	B4 train/test/positive/cells
Primary 1-km logistic	563/736/74/276	1299/1030/60/396	2329/988/38/384
2-km logistic	142/184/19/71	326/266/13/98	592/244/10/97
No early history	330/736/74/276	1066/1030/60/396	2096/988/38/384
Active front within 5 km	563/714/74/276	1277/941/60/394	2218/649/38/346
Perimeter within 2 km	151/285/60/116	436/479/55/182	915/624/33/203
Perimeter within 5 km	564/876/74/280	1440/1346/60/421	2786/1686/38/496
Boundary exclusion 1000 m	452/519/6/234 NE	971/730/2/332	1701/634/1/292
Boundary exclusion 500 m	496/599/23/252	1095/871/12/362	1966/809/7/336

658 Four held-out intervals per block. RF uses exactly the primary 1-km support. Primary held-out support per role:
659 2754 observations, 172 positives, 610 distinct cells and 12 intervals; full primary candidate universe: 3317 occasions
660 on 642 cells. These are repeated cell observations, not independent spatial replicates. NE counts describe eligible
661 data, not generated predictions.

662

663 ***Supplementary table S2 Post hoc representation models***

Descriptive model	Label	Log loss	Brier	Average precision	ROC AUC
Broad fuel families	A*	0.364791	0.108352	0.492152	0.933839
Broad fuel families plus EVT	B*	0.364601	0.108316	0.492823	0.933968
Native fuel categories	C*	0.365195	0.108479	0.489112	0.933674
Native fuel categories plus EVT	D*	0.364919	0.108420	0.488675	0.933643

664 POST HOC / EXPLORATORY. All four retain the same non-fuel baseline fields, observations, chronological
665 histories and original five EVT fractions where indicated. A*/B* use broad fuel; C*/D* use native FBFM40
666 fractions. All composition blocks use fixed orthonormal Helmert contrasts without division by training SD; other
667 numerical preprocessing is training-only. Design sizes: 25/29/65/69. These are not the primary models, whose
668 preprocessing differs. All 12 final exploratory choices selected C=0.1; original saved 40 tuning + 12 final fits were
669 reused, not rerun.

670

671 ***Supplementary table S3 Descriptive categorical information***

Quantity	Bits	Support
H(detailed EVT native fuel code)	2.347857	642 unique cells; 642 km2
H(detailed EVT broad fuel family)	3.266790	642 unique cells; 642 km2
Additional conditional information lost by grouping	0.918933	642 unique cells; 642 km2

672 POST HOC / EXPLORATORY. Physical-area weighting on unique spatial support; logarithms base 2. There are 87
673 detailed EVT classes and 27 observed fuel codes. The predictive models use five broad EVT fractions, not 87
674 detailed-class indicators. The old unpooled family entropy is superseded by the closure audit. Descriptive
675 information loss is not evidence of a propagation-relevant predictive penalty.

676

677 ***Supplementary table S4 Post hoc paired comparisons***

Comparison	Metric	Benefit	95% interval L=2	95% interval L=3
EVT benefit with broad fuel	Log loss	0.000190	[-0.000468, 0.001105]	[-0.000363, 0.001199]
EVT benefit with broad fuel	Brier	0.000036	[-0.000147, 0.000282]	[-0.000116, 0.000311]
EVT benefit with native fuel	Log loss	0.000276	[-0.000280, 0.001095]	[-0.000201, 0.001186]
EVT benefit with native fuel	Brier	0.000059	[-0.000095, 0.000278]	[-0.000072, 0.000309]
Broad minus native fuel	Log loss	-0.000403	[-0.001366, 0.000195]	[-0.001519, 0.000186]
Broad minus native fuel	Brier	-0.000128	[-0.000435, 0.000068]	[-0.000477, 0.000056]
Broad plus EVT minus native plus EVT	Log loss	-0.000318	[-0.001372, 0.000355]	[-0.001529, 0.000305]
Broad plus EVT minus native plus EVT	Brier	-0.000105	[-0.000435, 0.000117]	[-0.000477, 0.000091]
Broad EVT benefit minus native EVT benefit	Log loss	-0.000085	[-0.000190, 0.000029]	[-0.000176, 0.000030]
Broad EVT benefit minus native EVT benefit	Brier	-0.000023	[-0.000052, 0.000009]	[-0.000047, 0.000010]

678 All intervals include zero. A-B and C-D are EVT benefits; A-C and B-D are broad-minus-native losses (positive
679 favors native detail). Difference = (A-B) - (C-D), positive when EVT benefit is larger with broad fuel. Bootstrap
680 settings and temporal weighting match the saved exploratory procedure. No hypothesis, encoding or threshold was
681 selected from these results.

682

683 **Supplementary table S5 Post hoc block scores**

Model	Block	Log loss	Brier	Average precision	ROC AUC
Broad fuel families	B2	0.320238	0.088621	0.548026	0.921619
Broad fuel families	B3	0.559452	0.169891	0.503239	0.935023
Broad fuel families	B4	0.214683	0.066543	0.425193	0.944874
Broad fuel families plus EVT	B2	0.320160	0.088611	0.548386	0.921659
Broad fuel families plus EVT	B3	0.558092	0.169541	0.501893	0.935039
Broad fuel families plus EVT	B4	0.215552	0.066795	0.428190	0.945206
Native fuel categories	B2	0.320115	0.088625	0.548490	0.921873
Native fuel categories	B3	0.561276	0.170427	0.497581	0.934738
Native fuel categories	B4	0.214193	0.066386	0.421265	0.944412
Native fuel categories plus EVT	B2	0.320031	0.088614	0.548183	0.921780
Native fuel categories plus EVT	B3	0.559919	0.170077	0.496701	0.934239
Native fuel categories plus EVT	B4	0.214808	0.066571	0.421141	0.944909

684 POST HOC / EXPLORATORY. Each block averages its four saved interval metrics. All models have identical held-
685 out keys; all findings, including unfavorable B4 EVT contrasts, are retained. No supplementary figure is added
686 because the tables fully describe these completed comparisons.

687

688 *Supplementary table S6 Leave one interval out without refitting*

Metric	Omitted interval	Block	Full benefit	Omission benefit	Absolute change
brier		6 B2	0.000201	0.000182	0.000020
brier		8 B2	0.000201	0.000206	0.000005
brier		9 B2	0.000201	0.000194	0.000007
brier		10 B2	0.000201	0.000223	0.000022
brier		11 B3	0.000201	-0.000039	0.000241
brier		12 B3	0.000201	0.000048	0.000153
brier		14 B3	0.000201	0.000401	0.000200
brier		15 B3	0.000201	0.000395	0.000194
brier		16 B4	0.000201	-0.000067	0.000268
brier		18 B4	0.000201	0.000019	0.000183
brier		21 B4	0.000201	-0.000108	0.000309
brier		22 B4	0.000201	0.000961	0.000760
log loss		6 B2	0.000772	0.000766	0.000006
log loss		8 B2	0.000772	0.000917	0.000144
log loss		9 B2	0.000772	0.000798	0.000026
log loss		10 B2	0.000772	0.000608	0.000164
log loss		11 B3	0.000772	0.000108	0.000665
log loss		12 B3	0.000772	0.000114	0.000658
log loss		14 B3	0.000772	0.001395	0.000623
log loss		15 B3	0.000772	0.001472	0.000700
log loss		16 B4	0.000772	-0.000119	0.000892
log loss		18 B4	0.000772	0.000264	0.000508

Metric	Omitted interval	Block	Full benefit	Omission benefit	Absolute change
log loss		21 B4	0.000772	-0.000092	0.000864
log loss		22 B4	0.000772	0.003037	0.002265

689 No models were refitted. Omission recalculates the governed interval/block summary from existing primary paired
690 evidence; this is not a new predictive sensitivity.

691