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A Spatio-temporal model for burn severity data

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Objectives

1. This research presents a categorical spatio-temporal model for burn severity and ecosystem recovery. It takes as input satellite data acquired in the framework of the Monitoring Trends in Burn Severity (MTBS) project considering the period from 1984 to 2018.

2. Analyze the burn severity and recovery trends in the Oregon and Washington wildfire perimeters. A hand-coded variable (GRIDCODE) included in the database was produced by a team of analysts using an ordinal scale and processed satellite images. The burn severity scale has the following points: 1. Increased Greenness, 2. Unburned to Low, 3. Low, 4. Moderate and 5. High.

Material and Methods

The original MTBS database contains data on all significant wildfires in the US between 1984 and 2016. Here we considered a subset of nearly 4 million wildfires in the states of Oregon and Washington. A proportionally stratified sample was taken of 0.1% of the observations, using the Year as the stratification variable, resulting in a dataset of $n = 3910$ fires.

- ❑ A Generalized Linear Hierarchical Bayesian model with a spatio-temporal dependency component and mixed effects is used.
- ❑ Two different link functions are tested: cumulative logit and multinomial logit.

Material and Methods

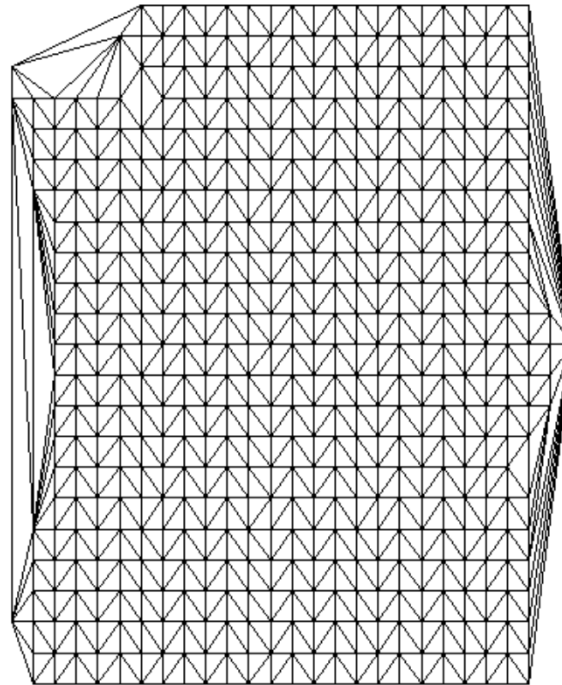


Figure 1: Delaunay Triangulation used to discretize the Oregon and Washington regions

Exploratory Analysis

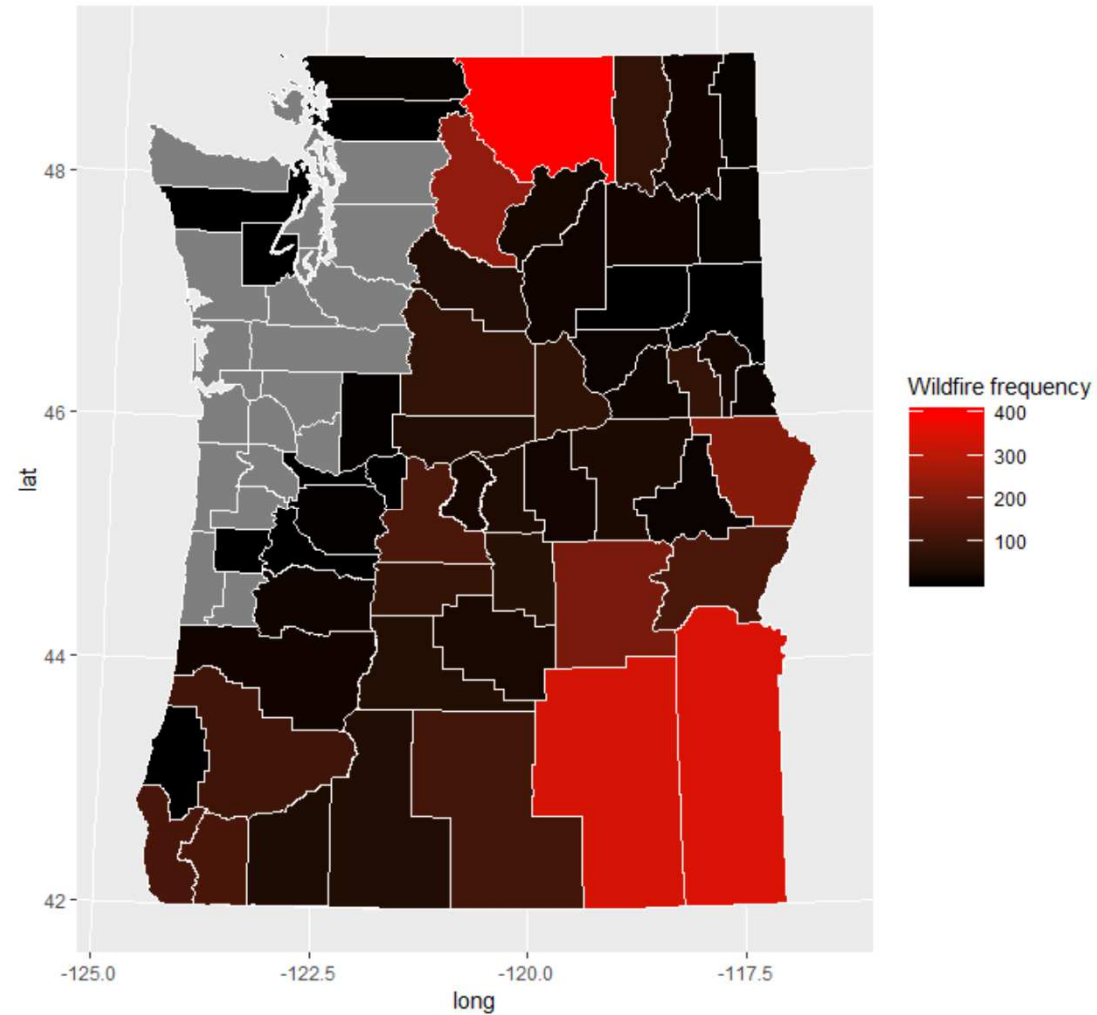


Figure 2: Frequency of Wildfires by County in the Washington and Oregon regions

Exploratory Analysis

To estimate the impact of the covariates and other wildfire attributes in the observed burn severity, we use a GLM with cumulative logit link. Results suggest that Existing Vegetation Type, Biophysical Settings, Elevation, 1-Week and 4-Week Average Temperature has a significant impact on Burn Severity.

	Coef	S.E.	Wald Z	p-value
$y \geq \text{Unb_low}$	5,3056	0,6149	8,63	<0,0001
$y \geq \text{Low}$	2,5993	0,6062	4,29	<0,0001
$y \geq \text{Moderate}$	1,0643	0,6048	1,76	0,0785
$y \geq \text{High}$	0,7891	0,6056	-1,3	0,1926
Acres	0,0002	0,0003	0,58	0,5651
Fuel	0,0001	0,0001	1,05	0,2945
Existing Vegetation Type	0,0007	0,0002	-4,49	<0,0001
Biophysical Settings	0,0008	0,0002	4,6	<0,0001
Landform	0,0226	0,0143	-1,58	0,1148
Mean Elevation	0,0003	0,0001	3,6	0,0003
Mean Slope	0,0006	0,0013	0,46	0,6435
1-Week Average Temperature	0,0517	0,0128	4,04	<0,0001
4-Week Average Temperature	0,0964	0,0215	-4,47	<0,0001
12-Week Average Temperature	0,0329	0,0151	2,19	0,0288

Results

We've applied two different families of link functions, and experimented with the impact of having no spatial component, spatial component only and a spatiotemporal component, resulting in 6 models to be tested (Table 1).

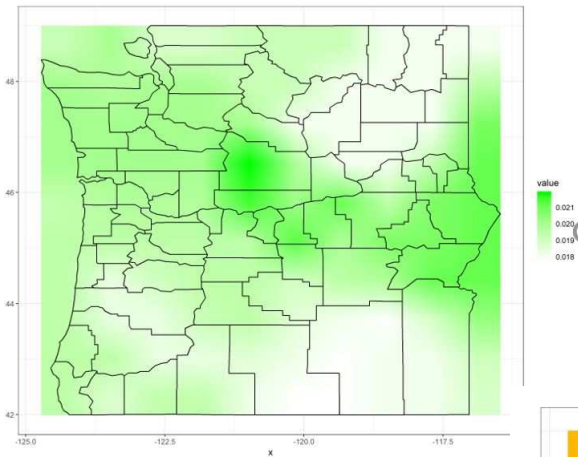
The models were compared using the WAIC metric (Table 2). The results suggest that Model 1A with cumulative logit link and the spatiotemporal component has the best fit of all six models.

	Multinomial	Cumulative
Hierarchical Bayesian Model with Spatiotemporal ICAR Component	Model 1A	Model 1B
Hierarchical Bayesian Model with Spatial ICAR Component	Model 2A	Model 2B
Hierarchical Bayesian Model	Model 3A	Model 3B

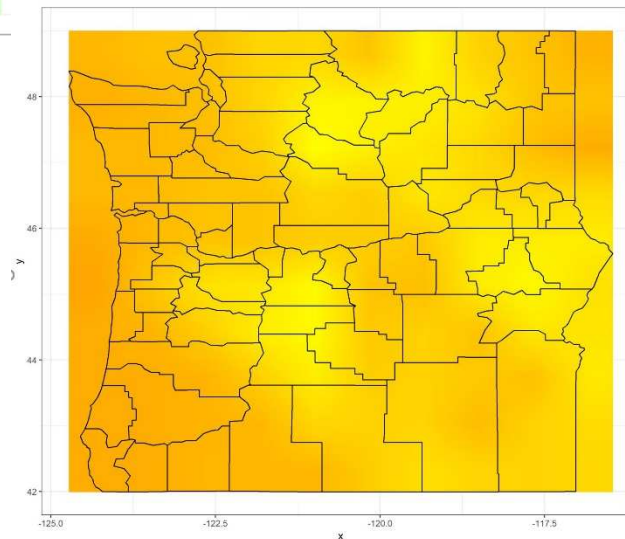
	Δ ELPD	Δ SE	WAIC	SE
Model 1A	0	0	8760	66,6
Model 2A	-23,3	8,6	8806,6	63,6
Model 2B	-32,8	7,7	8825,6	62,7
Model 3A	-37,6	12,9	8835,2	62,3
Model 3B	-48	11,2	8855,9	60,3
Model 1B	-465,8	49,5	9691,7	122,4

A final kriging procedure using Model 1A was conducted by estimating the probabilities of the different levels in different points of time and space. Applying a linear interpolation using inverse distance weighting and gaussian smoothing, we were able to obtain raster density surfaces for each level and year. Some examples of these results:

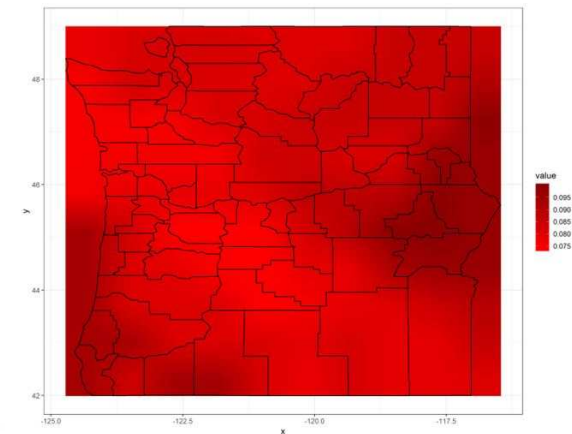
Increased Greenness



Low



High



Results

However, these results suggest that the ordinal properties of the scale might be poorly understood by the analysts, and thus resulting in a better fit of the multinomial logit model.

The estimated model coefficients along with the analysis in the previous sections seem to suggest that the temporal component has a larger impact in the model performance.

Therefore we could hypothesize that the temporal effect might be more important to explain observed burn severity. Additionally, the results confirm that the temporal component has a significant impact in the goodness of fit of the model, consistent with the observation of the temporal dependency and stationarity.

Results

Further improvements can be obtained by introducing the covariates, mainly the temperature (1-Week and 4-Week averages).

The analysis of the obtained kriging maps suggest that some observed burn severity seems to be associated with county level policies.

However, further research is required to make this methodology actionable for decision support in forest management, since the kriging maps suffer from a low resolution.

Future research

Explore the use of a different modelling approach (INLA) and a larger sample.

Incorporating the covariates we might also achieve improvements in model explanation and prediction.