Bayesian Analysis for Wildfire Classification in the United States and Australia Through Spatial Hierarchical Models

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Abstract. Wildfires in the United States and Australia burn upwards of ten million acres of land annually. Emitted carbon dioxide and smoke aerosol from wildfires damage the environment, and more than 46 million acres burned in the 2019–2020 Australian Wildfire season [5]. Predicting and forecasting wildfires can allow for proactive resource allocation, better public safety, and better decision making to marginalize these damages. NASA's Fire Information for Resource Management System (FIRMS) contains real time data of fires across the globe, in Australia and other regions. 153,916 and 156,417 fires were captured through NASA's MODIS instrument in 2020 in the United States and Australia, respectively (https://firms.modaps.eosdis.nasa.gov). Statisticians and other researchers have shown that we can successfully predict wildfires from various predictors, including vegetation data [6]. Other studies show that dry conditions and human activity are the leading causes of the wildfires. We create hierarchical models to predict wildfires given land and atmospheric conditions to assess and compare likely causes across continents. Hierarchical models allow us to take advantage of interpretable coefficients, so that we can determine the best predictors of wildfires and study the transferrability of wildfire climate relationships across continents. We apply a small amendment to the Hamiltonian Monte Carlo Method, introducing a severity weight to errors after taking the gradient to give us further insights into which predictors lead to the brightest wildfires. In total, we assess a Spatial Hierarchical Model, a Brightness Sensitive Spatial Hierarchical Model, and a Mixed Effects Hierarchical Model. Finally, we assess our models compared to state of the art, achieving 100% and 88.7% accuracy in wildfire prediction with a Bayesian Multilevel (hierarchical) Regression Model in Australia and the United States on complete data, respectively, an improvement over the 96.9% accurate Bayesian logistic regression model in Australia in 2023 [4], and outperforming deep neural networks with up to 90% accuracy trained on similar data in 2024 [10].

Keywords: Bayesian Modeling · Data Mining · Machine Learning · Deep Learning · Climate

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1 Introduction

Wildfire prediction is a critical application of machine learning. A wildfire is an instance of unplanned, uncontrolled, burning in natural vegetation, a phenomenon that has been around since the Silurian era [15]. Nevertheless, they are an integral component of terrestrial ecosystems. Fire behavior scientists have used mathematical models in the past to study its behaviors [1]. Early work from 1946 to 1973 focused on growth rate given different fuels. Nomographs to calculate fire behavior date back to as early as 1976.

Statistical Methods have an important role in wildfire prediction. Techniques employing Generalized Additive Models demonstrated success in a 2013 paper on wildfire prediction [15]. Random Forests, Support Vector Machines, KNN, and Bayesian Logistic Regression, and other models have also been successfully applied. Most recently, in 2024, Wildfire Classification in Morocco through feedforward neural networks with 3 hidden layers, 256 weights per layer, and a dropout rate of 60% achieved a high accuracy, up to 89.94% [10]. Alterations of number of hidden layers, weights per hidden layer, activation function, and dropout percent hit the $88\% - 89.4\%$ range, besting classical machine learning methods.

Bayesian Hierarchical Models are statistical tools that analyze complex, nested data [4]. The R programming language provides the BRMS (Bayesian Regression Models using 'STAN') library to offer full Bayesian Inference, a statistical method for which probability is updated as more information becomes available. The BRM model fits coefficients for our predictors by computing the posterior of our parameters, $p(\beta_1, \beta_2 ... \beta_p | X)$, in order to provide posterior predictive probabilities θ.

Unlike neural networks, Bayesian Hierarchical Models provide interpretability into their decision making process. The coefficients give us insight into the response curves, which allows for a comparison in the wildfire prediction process across two different models. We train Bayesian Hierarchical Models in the United States and Australia to assess the accuracy of results and the transferrability of wildfire-climate relationships across these continents.

2 Prior Work

Several iterations of state of the art wildfire prediction have been published since the 1900's [1]. Deep neural network architecture handled the problem efficiently in a 2024 paper, with most configurations outperforming classic machine learning techniques [10]. Another team in 2024 introduced convolutional neural networks and long short term memory networks, achieving as high as 98.6% accuracy [2].

Predictors for wildfire classification have also been the focus of studies in different regions. A previous study of bayesian analysis of wildfire classification in Australia reveals that the Normalized Difference Vegetation Index (NDVI) showed the strongest positive correlation with wildfire occurrence [5]. Soil moisture has also proven useful [10]. Other publications have used statistical signifi-

cance tests to show that some conditions, such as heat and humidity, create high favorability for fire ignition and propagation [11].

The transferability of wildfire climate relationships across continents has yet to be studied. While deep neural networks generally prevail, Bayesian Hierarchical Models have been sparsely tested in both the United States and Australia. In this paper, we use Bayesian Hierarchical Models and their interpretable parameters to compare wildfire posterior prediction across two countries, the United States and Australia.

3 Methodology

3.1 Data

Wildfire prediction depends on data specific to time and geolocation. We collect wildfire observation data from NASA's FIRMS and collate it with rich, available data from Google Earth Engine and other third party API's. We use data available at a single point in time, such that prediction is irrelevant to time or lag; this avoids unnecessary complexity. The dataset focuses on the following.

- **NDVI** - Normalized Difference Vegetation Index, provided by Google Earth Engine[1], captured through NASA's MODIS instrument.
- **Soil Moisture**- SMAP Level 4 soil moisture data, provided by Google Earth Engine[2], as collected by NASA.
- **Temperature** - Daily temperature data.
- **Cloud Cover** - Daily cloud cover data.
- **Humidity** - Daily humidity data.
- **Precipitation** - Daily precipitation data.
- **Elevation** - Topographic elevation data from Google Earth Engine, captured by NASA.
- **Wind** - Daily wind data.
- **City** - City data, matched by geolocation.
- **State** - State data, matched by geolocation.
- **Population** - Population data of a matching city.
- **Daynight** - A binary variable only true if the fire occurs during daylight.
- **Geolocation** - Geolocation as stored by NASA in FIRMS.

We start by collecting all wildfire data for our chosen countries in 2020 through NASA's MODIS Instrument. These datasets contain all times and locations at which a wildfire was captured. We consider the space of all times and locations in a country, and its subset, the space of all times and locations in which a wildfire is captured. We sample one thousand points from this subset and one thousand points from its complement; the sampled data maintains the same distribution of time stamp, brightness, and other predictors, which keeps the dataset balanced and realistic.

[1] https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MOD13A1.

[2] https://developers.google.com/earth-engine/datasets/catalog/NASA_SMAP_SPL4SMGP_008.

3.2 Exploratory Data Analysis

Exploratory Data Analysis on wildfires in the dataset for Australia and United States shows that the distribution of the variance is well spread throughout each of 9 predictors, excluding geolocation, population, state, and city; not all observations in the data match to a city. Principal Component Analysis, a dimensionality reduction technique that identifies the direction of maximum variance, reveals that temperature and wind have a strong positive correlation in both the United States and Australia. Soil moisture, NDVI, and humidity are also positively correlated, with projections onto the biplot that point in a different direction. Cloud cover and precipitation also show some correlation, albeit of a smaller magnitude; these similarities also persist across both countries (Fig. 1).

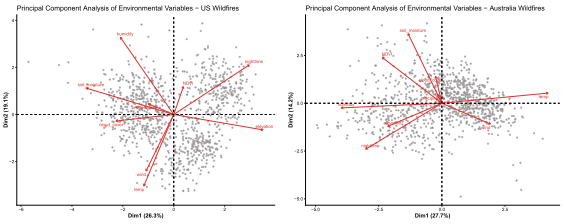


Fig. 1. Principal Components Analysis on wildfire data in the United States (Left) and Australia (Right).

Multicollinearity exposes problems in the interpretability of coefficients as it often hides the impact of individual predictors. The Variation Influence Factor (VIF), as calculated for a generalized linear model, for all 9 predictors stays below a magnitude of 3 in every country. Humidity in Australia is the only predictor to have a VIF greater than 2. We therefore conclude that multicollinearity should not damage the interpretability of our coefficients (Table 1).

3.3 Hierarchical Model

We use a hierarchical model for classification of wildfires. These models use our predictors as random variables, and each have coefficients. A hierarchical model takes raw random variables, multiply them by their coefficients, adds them, and applies an inverse logit function.

$$P(Wildfire|X) = logit^{-1}(\beta_1 X_1 + \beta_2 X_2 + ...\beta_p X_p)$$

The higher the score, the higher the probability. Our models are therefore interpretable, as, higher coefficients and high values of the predictors indicate a higher probability of a wildfire. Figure 2 shows example probability density function, $P(Wildfire|X)$, as characterized by an inverse logit function.

A simple Bayesian Logistic Regression model has an equation that consists of coefficients and random variables. In a Bayesian hierarchical model, random

Table 1. Variance Inflation Factor (VIF) values for environmental predictors in Australia and the US.

Variable	Australia	US
Temperature (°C)	1.7988	1.5057
Wind	1.0978	1.1070
Humidity	2.0280	1.4464
Night Time	1.1151	1.2585
Elevation	1.1096	1.9330
Soil Moisture	1.4075	1.5724
NDVI	1.5837	1.2285
Cloud Cover	1.1516	1.2359
Precipitation	1.0347	1.1280

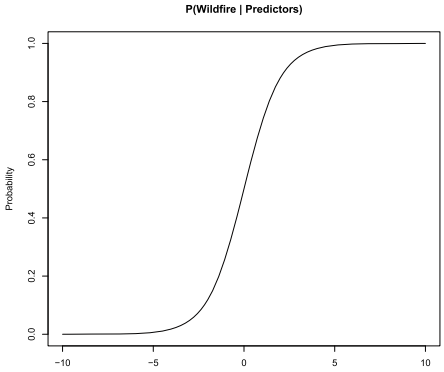


Fig. 2. A graphical display of a probability density function represented by the inverse logit function. As values get higher, probability converges to 1. As values get lower, probability converges to 0.

variables build on top of each other; i.e., they help define the distribution of random variables higher up. The final outcome is always fed into the logit function, which produces a probability between 0 and 1.

3.4 Spatial Kernel

The Bayesian hierarchical models consider geolocation through a spatial kernel. In addition to the linear model of the coefficients and their predictors, we add a spatial kernel that takes in latitude and longitude, then feets them into a spline with k knots. The spline fits a 2D space; parameters inside the kernel are optimized with the model's other parameters.

3.5 Hamiltonian Monte Carlo

The Hamiltonian Monte Carlo is a method that uses the derivatives of the density function being sampled to generate efficient transitions spanning the posterior. It produces optimal coefficients for our predictors, which make the model interpretable.

Algorithm 1. Hamiltonian Monte Carlo

Require: Original parameters θ_0
Ensure: Optimal parameters $\theta_{t_{final}}$
1: $\rho \sim \mathcal{N}(0, 1)$
2: Leapfrog Method:
$\rho_{t+\frac{\epsilon}{2}} = \rho_t - \frac{\epsilon}{2}\nabla_\theta U(\theta_t)$
$\theta_{t+\epsilon} = \theta_t + \epsilon\rho_{t+\frac{\epsilon}{2}}$
$\rho_{t+\epsilon} = \rho_{t+\frac{\epsilon}{2}} - \frac{\epsilon}{2}\nabla_\theta U(\theta_{t+\epsilon})$, where ϵ is the step size.
3: Repeat the leapfrog steps L times to propose a new state $(\theta_{new}, \rho_{new})$.
4: Compute the Metropolis acceptance probability:
$\alpha = \min\left(1, \exp\left[-H(\theta_{new}, \rho_{new}) + H(\theta, \rho)\right]\right)$.
5: Accept the new state with probability α. Discard the momentum variable and repeat.

We use the Hamiltonian Monte Carlo Method provided in the BRMS library, as well as implement it in Python for customization. These methods give us interpretable and optimal coefficients to build a function that calculates the probability that a given observation is a wildfire.

4 Results

A Bayesian framework offers robust evaluation. Test data provides evaluation on predictive performance for unseen data. We divide our data into a 60/40 test split, and conduct analysis for variations of 3 Bayesian Models: 1) Spatial Hierarchical model, 2) Brightness Sensitive Hierarchical Model, and 3) Mixed Effects Spatial Hierarchical Model.

4.1 Spatial Hierarchical Model

The spatial hierarchical model on the United States and Australia produces accuracies of 88.58% and 86.69% on wildfire prediction, respectively. The United States has a true positive rate of 0.914 and a true negative rate of 0.857; precision is 0.866 and recall is 0.914. Australia has a true positive rate of 0.918 and a true negative rate of 0.71621622; precision is 0.905 and recall is 0.918. Varying the threshold for which a probability predicts a positive wildfire classification creates an AUC of 0.9378 and 0.9161 on an ROC curve in the United States and Australia, respectively (Fig. 3).

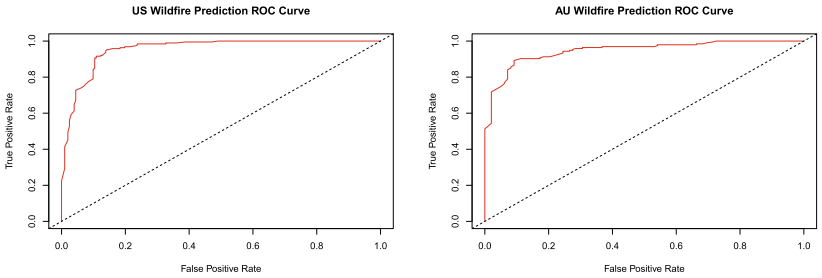


Fig. 3. ROC curves for wildfire prediction with a shifting threshold, θ. The United States has an AUC of 0.9378 compared to Australia's AUC of 0.9161.

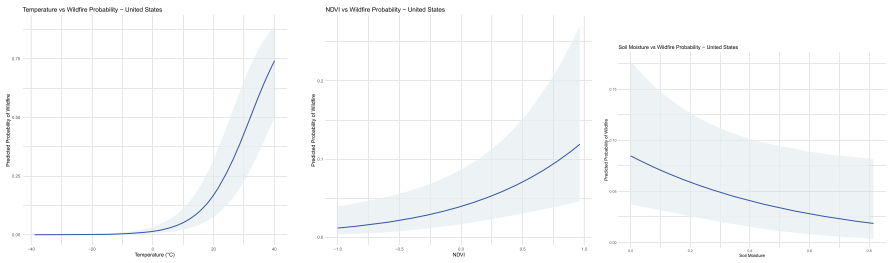
To compare wildfire prediction in the United States and Australia, we compare the response curves for different predictors of wildfires in both countries. A response curve shows the probability of a wildfire produced for different values of a predictor, for example, $P(Wildfire|Wind = x)$. Response curves for the United States and Australia are shown below. Overall, the United States shows steeper positive curves with lower confidence intervals.

The coefficients show that temperature and NDVI have the highest positive contribution to wildfire probability. Soil Moisture has the highest negative contribution. This is consistent in both the United States and Australia, although soil moisture has a negative contribution of much greater magnitude in Australia than the US (Table 2).

Table 2. Coefficient Estimates for Spatial Hierarchical Models.

Variable	United States	Australia
Temperature (°C)	0.13	0.12
Wind	−0.05	−0.03
Humidity	−0.04	−0.02
NDVI	1.24	1.47
Precipitation	−0.47	0.54
Cloud Cover	−0.01	−0.01
Soil Moisture	−1.90	−6.58
Elevation	0.00	0.00
Night Time	−0.96	−0.85

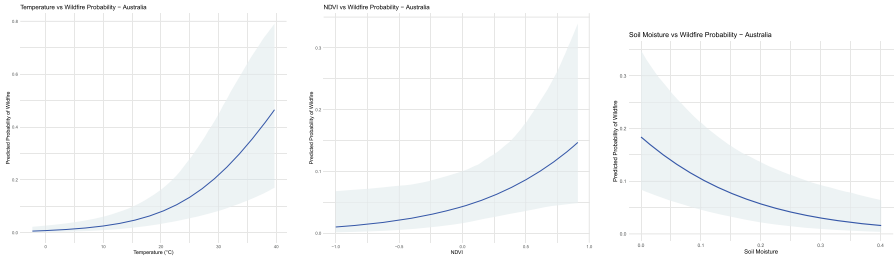
Just as the response curves show, our coefficients for the predictors reveal that wildfire probabilities in the United States have the highest positive contribution from NDVI, and then temperature. Soil Moisture has the highest negative contribution. The maps in Fig. 5 show the classifications of all wildfire data after training on the full dataset (Fig. 4).



(a) P(W | Temp (°C)) - United States

(b) P(W | NDVI) - United States

(c) P(W | Soil Moisture) - United States



(d) P(W | Temp (°C)) - Australia

(e) P(W | NDVI) - Australia

(f) P(W | Soil Moisture) - Australia

Fig. 4. Response curves for wildfire probability with respect to various predictors across countries. While wildfire probability goes down quicker with soil moisture in Australia, NDVI and Temperature both consistently increase wildfire probability across countries.

4.2 Brightness Sensitive Spatial Hierarchical Model

We apply an amendment to the Hamiltonian Monte Carlo Algorithm. By applying a weight to the errors ϵ when calculating the gradient, the algorithm updates coefficients in the direction of the steepest ascent for the brightest wildfires.

$$\epsilon_i = \frac{\text{brightness}_i}{\max(\text{brightness})}\,\epsilon_i$$

Observations not labelled as a wildfire are weighted as $0.4 * \epsilon_i$, as they have no brightness. The coefficients produced from training a model on this algorithm will show us predictors of brighter wildfires, as opposed to focused solely on the optimum decision boundary. By comparing coefficients to the spatial hierarchical model, we may study which factors drive brighter wildfires, instead of just contributing to the probability of a wildfire.

Wildfire classification results remained starkly unchanged, albeit somewhat lower, with the amendment; we use the same 60/40 train and test data ratio to compute metrics. Test accuracy in the United States is 84.125%, with a true positive rate of 0.881, a true negative rate of 0.801, a precision of 0.818, a recall

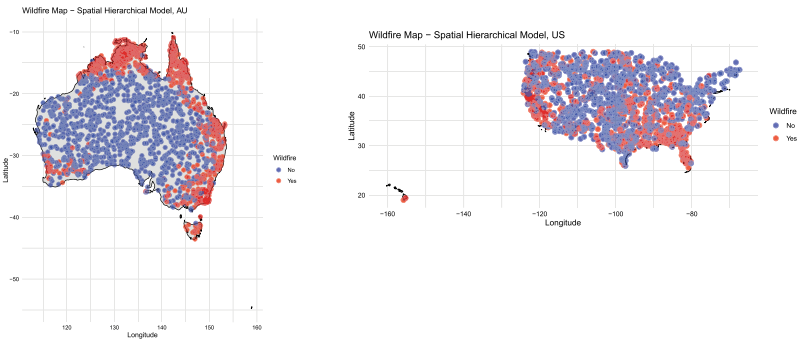


Fig. 5. Wildfires from the dataset as classified by the Spatial Hierarchical Model.

of 0.881, and an F1 score of 0.848. Test accuracy in the Australia is 77.22%, with a true positive rate of 0.780, a true negative rate of 0.765, a precision of 0.772, and a recall of 0.780, and an F1 score of 0.776 (Table 3).

Table 3. Comparison of United States and Australia model coefficients.

Variable	United States	Australia
Temperature (°C)	0.1545	0.0779
Wind	−0.0446	−0.0658
Humidity	−0.0226	−0.0113
NDVI	−0.0311	2.986
Precipitation	−0.0804	−0.3373
Cloud Cover	−0.0120	−0.0021
Soil Moisture	0.0106	0.5016
Elevation	0.00028	0.0006
Night Time	−0.01004	−0.7625

While wildfire accuracy goes down somewhat, the coefficients give us a closer look at the brightness sensitive trained spatial hierarchical model. In other words, we trade accuracy for different interpretability. The coefficient for temperature is higher in the United States than it is for the regular spatial hierarchical model. In the United States, a 95% credible interval for the temperature coefficient is [0.1545, 0.1652] for the brightness sensitive model, while the regular hierarchical spatial model has a 95% credible interval of [0.11, 0.15]; we therefore have significant evidence to conclude that hotter temperatures predict brighter wildfires in the United States. Our results match the Stefan-Boltzmann Law, which indicates that fire luminosity increases with temperature [8]. The other two biggest contributors, NDVI and soil moisture, converge closer to 0 than in the Spatial Hierarchical Model.

This indicates that temperature tells us which fires are brighter in the US, while the coefficients give us little indication of what contributes to a wildfire's brightness in Australia. Furthermore, the hottest regions in Australia, the center, have the fewest wildfires, which prevents the brightness sensitive model from relying on temperature as strongly as it does in the United States. For this reason, we conclude that only the United States shows that the Brightness Sensitive Spatial Hierarchical Model can be used to indicate which predictors predict brighter wildfires (Fig. 6).



Fig. 6. Wildfires classified by the Brightness Sensitive (Top Left) and Regular Spatial Hierarchical Model (Top Right) in the US; the bottom row shows Australia in the same order. The true positive rate is 0.881, compared to 0.914 in the US. The Brightness Sensitive Model raises $P(Wildfire)$ with higher temperature - the model catches an extra true positive case in Hawaii, potentially because of the modification. It is misclassified with the regular model; we show Alaska and Hawaii in these images to observe all misclassifications impacted by brightness.

4.3 Mixed Effects Hierarchical Model

Finally, we introduce a Mixed Effects Hierarchical Model. The Spatial Hierarchical Model is successful, however, it does not take advantage of the multilayered

structure component of a Bayesian Hierarchical model. We can, in fact, provide an extra coefficient for each predictor, dependent on another predictor. This gives our models the flexibility to have different impacts of land and atmospheric conditions by city and state. It potentially, serves as a replacement for the spatial kernel.

A Mixed Effects Hierarchical Model can add group effects for state and city. Group effects are when we have random variables with, for example, K different classes. We therefore have K extra parameters, and add them to our probability function. A random intercept is a parameter added to the probability equation; a random slope is a parameter, from a predictor such as city or state, that is added to a predictor's coefficient before multiplication.

One example is a Mixed Effects Hierarchical Model with a random intercept for city and a random slope for soil moisture at the city level. The extra random variables are defined below.

$$\alpha_{state[j]} \sim \mathcal{N}(0, \sigma^2_{state})$$

$$\alpha_{city[j]} \sim \mathcal{N}(0, \sigma^2_{city_1})$$

$$\beta_{\text{soil moisture, } city[j]} \sim \mathcal{N}(0, \sigma^2_{city_2})$$

$$(\beta_{\text{soil moisture, } city[j]} + \beta_{\text{soil moisture}}) X_{\text{soil moisture}} + \alpha_{city[j]} + \alpha_{state[j]} + \beta_1 X_1 + ... \beta_p X_p$$

We define a Mixed Effects Hierarchical Model with a random intercept for city and state, and a random slope at the city level for each predictor. When city and state data is not missing, these models reach 100% classification accuracy on our 60/40 train and test split in Australia, and reach as high as 88.7% in the United States. The ROC curves below show perfection in Australia and success in the US (Fig. 7).

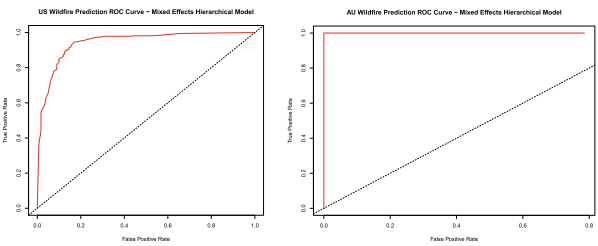


Fig. 7. ROC curves for wildfire prediction with a shifting threshold, θ on the Mixed Effects Hierarchical Model. The Australian model has a perfect score, leading to a square shape and an AUC of 1. The US has an AUC of 0.9448.

Overall, the Mixed Effects Hierarchical Model reaches an accuracy of 100% in Australia; this is equivalent to a true positive rate of 1, a true negative rate of 1, a precision of 1, and an F1 score of 1. The Mixed Effects Hierarchical Model reaches an accuracy of 88.7% in the United States, with a true positive rate of 0.9084,

a true negative rate of 0.867, a precision of 0.8653, a recall of 0.9084, and an F1 score of 0.8863346. Some observations fail to map to a city and state during the geocoding stage of preprocessing. The Mixed Effects Hierarchical Model with some missing city or state data produces classifications with accuracies of 84.06524% and 88.25% in Australia and the United States, respectively (Fig. 8).

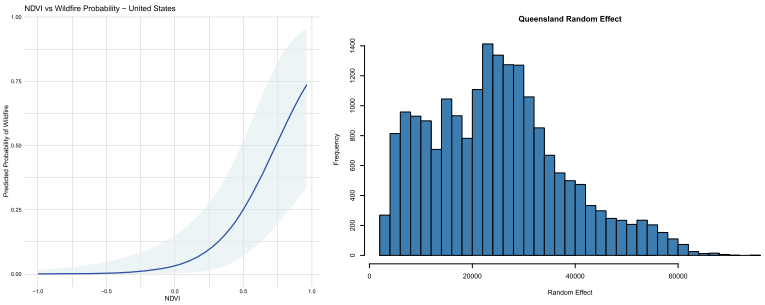


Fig. 8. Response curves for wildfire probability with respect to various predictors across countries. The NDVI response curve in the United States indicates a strong positive contribution with the city and state effects. The mixed effects hierarchical model for Australia is more dependent on the state, with less emphasis on the predictors.

The response curves visualize the relationship between predictors and wildfire probability in the United States. The states are stronger indicators of wildfire probability in Australia. They minimize the impact of the predictors; random effects for Australian states range from -7018.58 to 22246.17, while random effects for American states range from -6.68 to 4.76. Therefore, the response curves in the United States show that probability of a wildfire heavily depends on predictors, in Australia, the state and city effects dominate.

4.4 Model Checking

A one parameter model is a class of sampling distributions indexed by a single unknown parameter θ [9]. A Bayesian Hierarchical model provides a posterior from the training data that shows the probabilities of a wildfire per each individual observation. If the one parameter model for number of wildfires is a binomial distribution with parameter θ representing wildfire probability, then θ has a beta distribution with shape parameters α and β representing number of wildfires and non wildfires, respectively. The shape parameters in the prior, before seeing data, approximate 0.5 as a likely θ. The posterior updates the distribution with data from the dataset, estimating a θ of 0.709 and 0.5 in Australia and the United States, respectively. Figure 9 compares a one parameter model to the posteriors of all three Bayesian models in Australia and the United States.

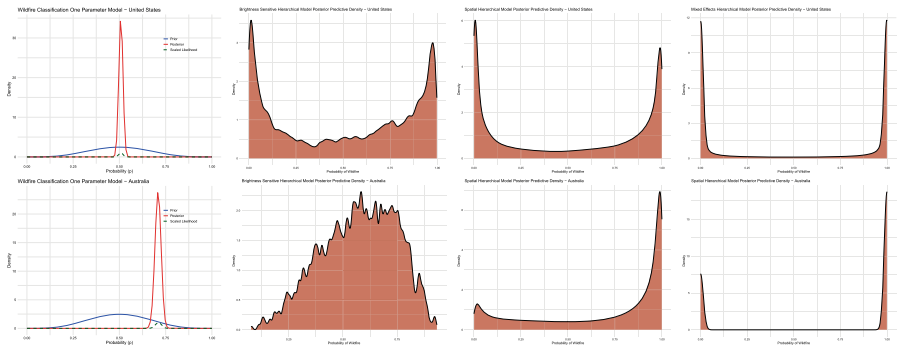


Fig. 9. A One Parameter Model for Wildfire Classification through a Beta Distribution (Left) followed by Posterior Predictive Densities in the United States (Top) and Australia (Bottom). Most Bayesian models produce a θ that clearly indicates if an observation is a wildfire or not.

4.5 Sensitivity Analysis

We apply a prior of $\mathcal{N}(0, 1)$ to the models in Australia and the United States. The coefficients do not deviate significantly when the models use a strong prior. Accuracies are 83.6%, 88.6%, 88.3% in the United States, ordered by their posteriors in Fig. 10. Accuracies are 65%, 85.6%, and 100% in Australia. The posteriors do not deviate significantly in shape. This means that the likelihood dominates the prior, our data is informative, and our conclusions from earlier are robust.

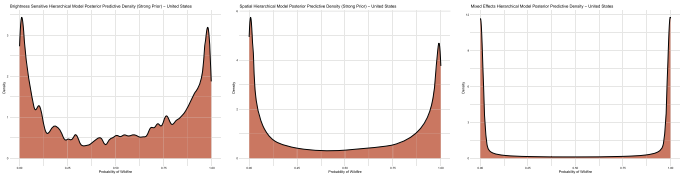


Fig. 10. The Prior has little impact on the posterior. Posteriors for the United States are shown above, almost matching posteriors without a prior added; Australia also matches its normal posterior.

4.6 Simulations

We measure the wildfire forecasts produced by the models by simulating land and atmospheric conditions throughout a country, and comparing the maps produced. After sampling random locations from the country, we add predictors randomly sampled, with replacement, from the full dataset. The Wasserstein distance metric measures the similarity between the wildfire maps; it is the minimum cost of transforming one probability distribution of wildfires to another.

We can use Wasserstein distance to measure how similar wildfire maps from all three models are on random data. They also show how dominant some geolocation regions are in each model; these simulations are featured in Fig. 11. They show how city, state, and geolocation differ in determining wildfire probability.



Fig. 11. Wildfire simulations: Top row shows Australia, bottom row shows the United States. Wasserstein distance for models are, left to right, 3.91 (Spatial Hierarchical Model), 4.96 (Mixed Effects Model), and 10.48 (Brightness Sensitive Model) in Australia. In the United States, they are 15.56 (Spatial Hierarchical Model), 16.32 (Mixed Effects Model), and 9.48 (Brightness Sensitive Model).

4.7 Comparison

Our best models score above 86% accuracy in all countries on test data. Another Bayesian model from 2022, which emphasized the positive contribution of NDVI to wildfire probability, resulted in 96.9% accuracy; the mixed hierarchical model introduced in this paper produces 100% accuracy with complete data. We reproduce many different configurations of deep neural networks previously and replicate experiments on our Australian and United States datasets from 2020 [10]. The results are displayed under the Bayesian Models in Table 4. Finally, we train classical machine learning models on the same data and compare them to the hierarchical and deep learning models; hierarchical models produce higher accuracies in both countries.

5 Conclusion

We conclude that many wildfire climate relationships transfer across continent. The exploratory data analysis shows that soil moisture and wind are projected into similar directions on a biplot of the first two principal components. Probability of a wildfire increases with temperature and NDVI. Soil moisture, meanwhile,

Table 4. Model performance by country.

Model	US	AU
Spatial Hierarchical Model	88.58	86.69
Brightness Sensitive Hierarchical Model	84.125	77.22
Mixed Effects Hierarchical Model 1*	88.7	100
Mixed Effects Hierarchical Model 2	84.07	88.25
Decision Tree Classifier	85.875	84.105
K-Nearest Neighbors	80.125	70.713
Support Vector Machine	72	67.459
100L-relu	83.875	75.34
4L-32U-0.2D-relu	86.37	82.98
3L-32U-0.2D-relu	85.5	85.61

* Results when city and state data are not missing (293 observations).

is much more indicative of no wildfires in Australia. These features are consistent across both countries, Australia and the United States. We introduce an amendment to Hamiltonian Monte Carlo, which gives us significant evidence to conclude that higher temperatures in the United States predict bright wildfires. This method can be extended to reach conclusions for similar categorical accuracy problems. Finally, we reproduce results from other papers. We show that Bayesian models can be more successful than deep neural networks, achieving up to 100% accuracy in Australia, and outperforming the best neural network architectures to date.

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