Wildfire Vulnerability Across Crop Types

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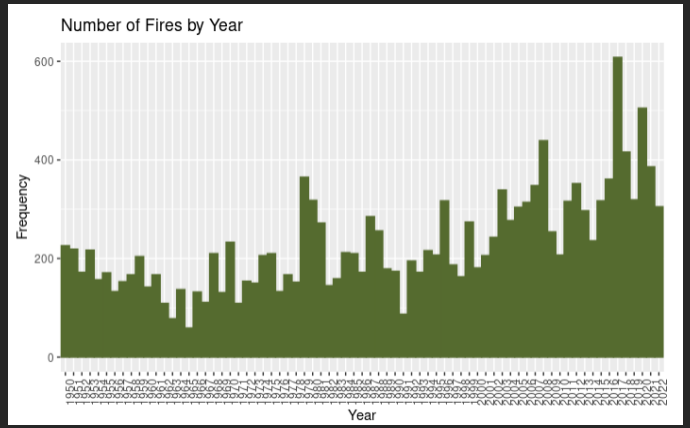
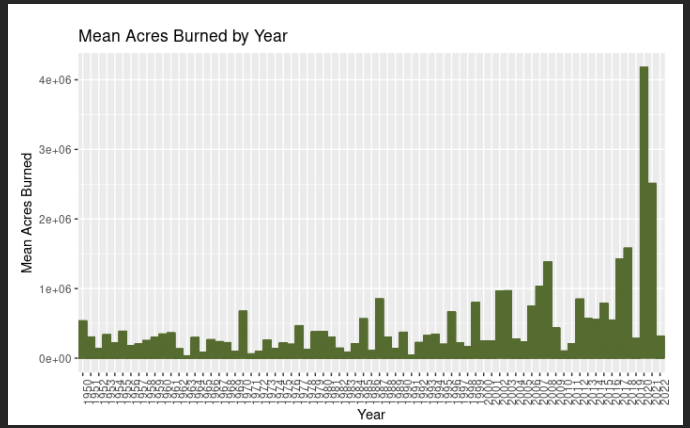
Question of Interest:

Are grapes or pastureland more susceptible to wildfires than other crops?

Significance:

- California leads the nation in agricultural exports
- Increasing severity and frequency of wildfires jeopardizes our most important resource: food





Spatial Data:

- Data with a geometry column
- Spatial data formats

Raster

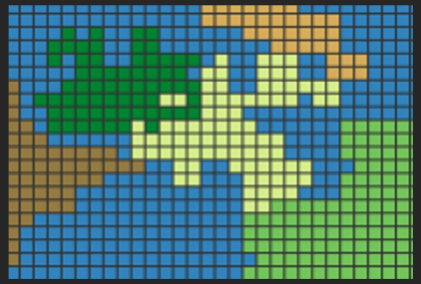


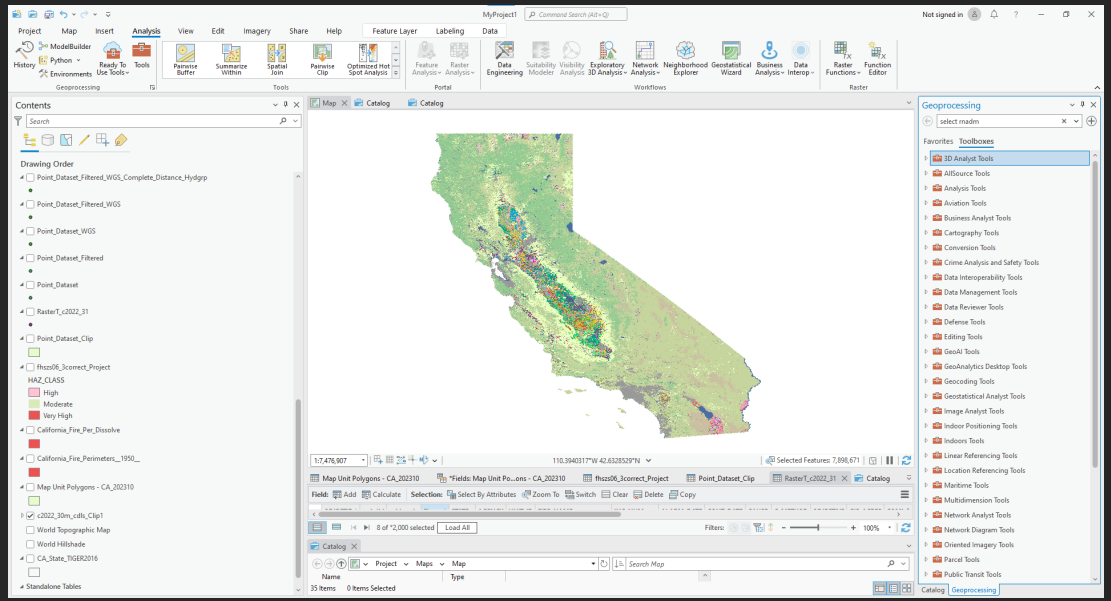
Image Source: ArcGIS

Polygon

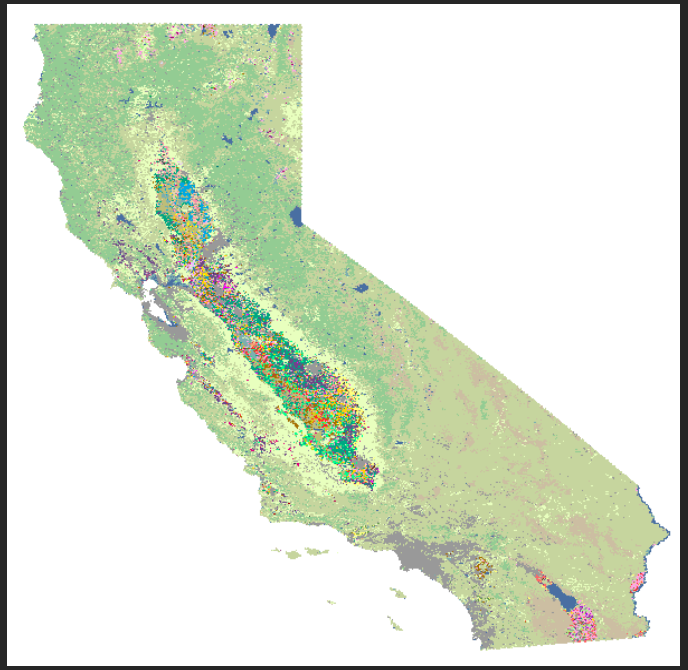
Image Source: ArcGIS

ArcGIS:

- What is ArcGIS?
  - Program developed for spatial data
  - Includes toolkits for data wrangling and modeling



Data Sources:

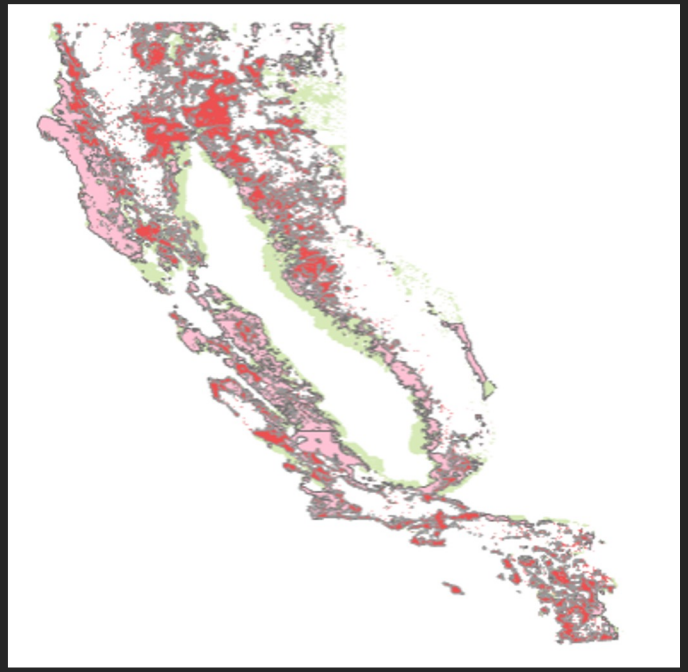


Crop Data: CropScape

Data Sources:

ObjectID	CropType	Geometry
10817	176	POINT (-2286900 2452680)
11067	176	POINT (-2286870 2452650)
11318	176	POINT (-2286900 2452620)
11321	176	POINT (-2286810 2452620)
11573	176	POINT (-2286900 2452590)
11832	176	POINT (-2286870 2452560)

Data Sources:



Fire Hazard Severity Zones Data: CalFire

Green = Moderate, Pink = High, Red = Very High

Data Limitation: NA's

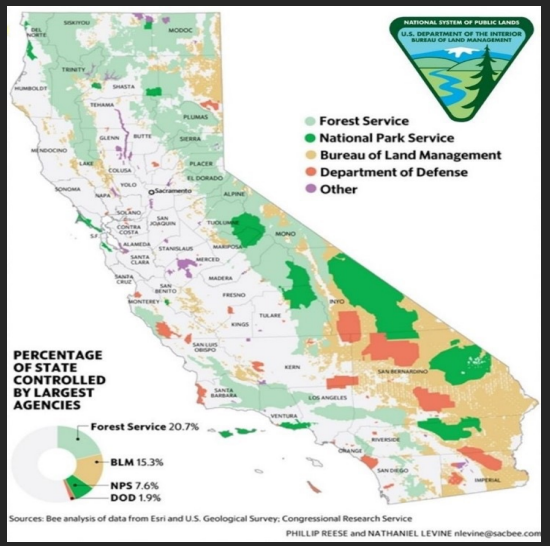
Data Sources:

ObjectID	HazardClassCode	HazardClass	ShapeLength	ShapeArea	Geometry
1	1	Moderate	2013.464	108898.67	POLYGON ((-1938430 1268163,...
2	1	Moderate	2758.326	148499.93	POLYGON ((-1938532 1271467,...
3	1	Moderate	2506.648	149217.93	POLYGON ((-1944405 1275171,...
4	1	Moderate	4256.729	157700.55	POLYGON ((-1887530 1261956,...
5	1	Moderate	9088.942	1084231.78	POLYGON ((-1908571 1268742,...
6	1	Moderate	1523.170	65261.64	POLYGON ((-1873286 1259942,...

Data Sources:

Soil Data: gSSURGO and Soil Toolkit

Large green areas represent public lands

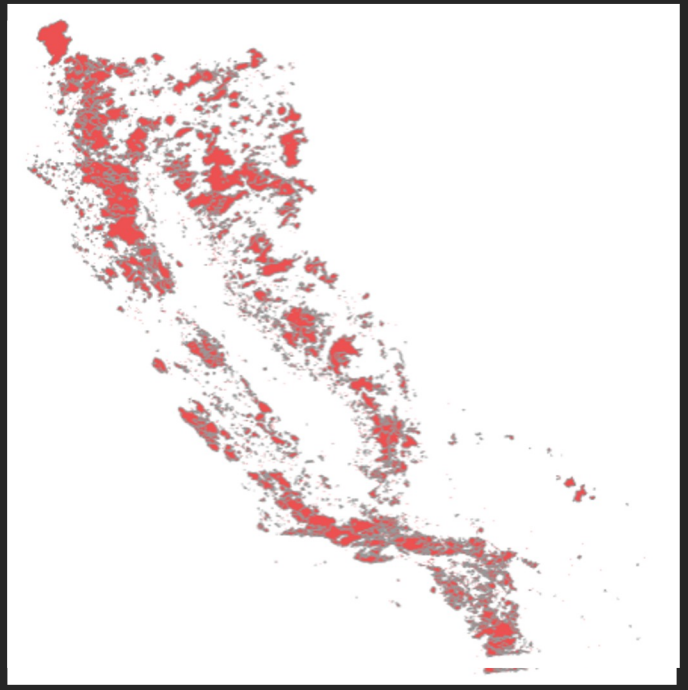


Public Lands

Data Sources:

ObjectID	ShapeLength	ShapeArea	SoilCompactionPercentage	NumberOfFrostFreeDays	HydrologicGroup	Geometry
1	6736.832	929159.1	25	225	C	POLYGON ((-2244979 2353731,...
2	8147.547	1052839.9	50	125	B	POLYGON ((-2208144 2353732,...
3	9901.538	1760741.4	5	NA	NA	POLYGON ((-2231336 2354345,...
4	4734.245	717553.4	35	175	A	POLYGON ((-2219626 2353632,...
5	3284.710	457928.2	5	NA	NA	POLYGON ((-2222754 2354433,...
6	6495.876	1382703.9	5	NA	NA	POLYGON ((-2237880 2353413,...

Data Sources:



Wildfire Data: California Open Data Portal

Data Sources:

ObjectID	Year	Name	Acres	ShapeLength	ShapeArea	Geometry
21440	2020	NELSON	109.60228	0.0357330	0.0000461	MULTIPOLYGON (((-121.3484 3...
21441	2020	AMORUSO	685.58502	0.1011780	0.0002878	MULTIPOLYGON (((-121.3528 3...
21442	2020	ATHENS	27.30048	0.0174496	0.0000115	MULTIPOLYGON (((-121.3333 3...
21443	2020	FLEMING	12.93154	0.0165571	0.0000054	MULTIPOLYGON (((-121.2732 3...
21444	2020	MELANESE	10.31596	0.0109196	0.0000044	MULTIPOLYGON (((-121.3007 3...
21445	2020	PFE	36.70193	0.0242667	0.0000154	MULTIPOLYGON (((-121.3824 3...

Data Wrangling Phase:

- Pre-Processing
- Variable Creation:
  - Leverage “Near” tool to create Distance variable
  - Implement “Calculate Geometry” tool to determine coordinates of each observation

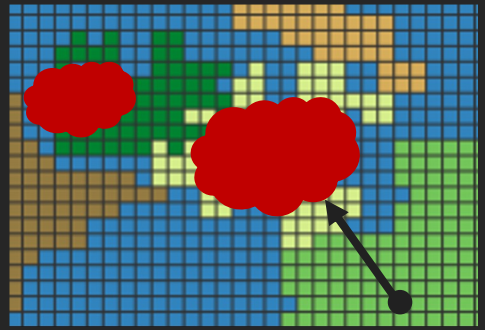


Image Source: ArcGIS

Dataset:

- Resampled data such that the final dataset has 2,500 complete observations (no NA values) for each crop type of interest: pastureland, grapes, and “other”

Distance	HazardClass	CropType	Latitude	Longitude	SoilCompactionPercentage	HydrologicGroup	NumberOfFrostFreeDays
0.0684000	Very High	grapes	-13726373	5138033	70	A	175
0.6064666	High	grapes	-13713814	5136558	35	A	175
0.2085428	Very High	grapes	-13602353	5160107	85	A	125
1.6253280	Very High	grapes	-13595986	5161887	85	C	90
1.6820752	Very High	grapes	-13595836	5161512	85	C	90
0.1916961	Very High	grapes	-13605195	5156181	85	A	125

Modeling Phase Set-Up:

- Employ 5 modeling techniques on Distance and Hazard Class response variables
  - Cannabis Study: Proxies for wildfire vulnerability
- Variables:
  - Crop Type
  - Number of Frost-Free Days
  - Latitude and Longitude
  - Soil variables:
    - M1: Soil Compaction Percentage
    - M2: Hydrologic Group

Preliminary Pixel-Level Modeling:

- Regress Distance on Crop Type, Number of Frost-Free Days, and soil variables
- Model A1:
  - $\widehat{Distance_i} = \beta_0 + \beta_1 CropType_i + \beta_2 Numberof FrostFreeDays_i + \beta_3 SoilCompactionPercentage_i + \in_i$
- Model A2:
  - $\widehat{Distance_i} = \beta_0 + \beta_1 CropType_i + \beta_2 Numberof FrostFreeDays_i + \beta_3 HydrologicGroup_i + \in_i$

Preliminary Pixel-Level Modeling Limitations:

- BUT… spatial autocorrelation error!
  - Spatial autocorrelation refers to neighboring points having similar values
- Moran’s I Statistic = .92
- Need to implement more appropriate modeling techniques

⚠ WARNING 000851: Use the Spatial Autocorrelation (Moran's I) Tool to ensure residuals are not spatially autocorrelated.

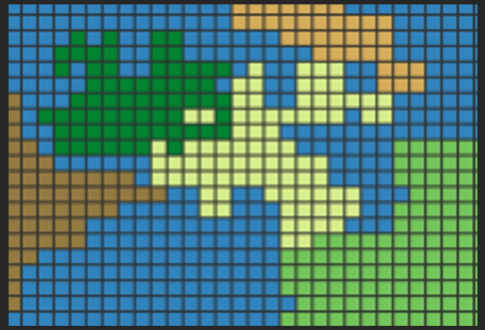


Image Source: ArcGIS

Remedy #1- Pixel-Level OLS:

- Expand on previous regression by including an interaction between Latitude and Longitude
- Model B1:
  - $\widehat{Distance}_i = \beta_0 + \beta_1 CropType_i + \beta_2 NumberofFrostFreeDays_i + \beta_3 SoilCompactionPercentage_i + \beta_4 Latitude_i + \beta_5 Longitude_i + \beta_6 Lattitude_i * Longitude_i + \in_i$
- Model B2:
  - $\widehat{Distance}_i = \beta_0 + \beta_1 CropType_i + \beta_2 NumberofFrostFreeDays_i + \beta_3 HydrologicGroup_i + \beta_4 Latitude_i + \beta_5 Longitude_i + \beta_6 Lattitude_i * Longitude_i + \in_i$

Latitude and Longitude Interaction:

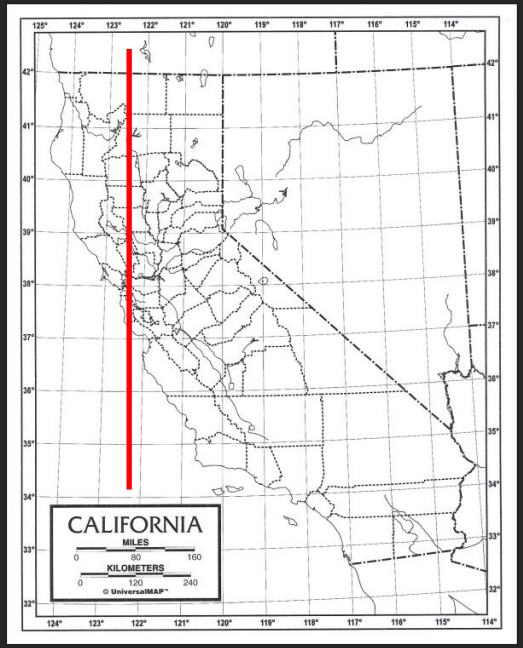
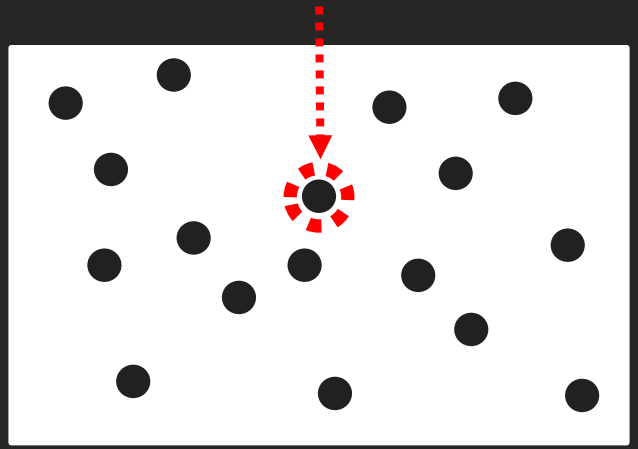


Image Source: Rainbow Reource

Remedy #2- GWR:

- Geographically Weighted Regression Framework
  - Relationships are not consistent over the study area, so calculates a regression model at each location
    - Tobler's Law: Borrowing neighboring values



Remedy #2- GWR:

- Utilize framework from preliminary pixel-level model, but allow for coefficients to be calculated at each point
- Model C1:
  - $\widehat{Distance}_i = \beta_{0i}(u_i, v_i) + \beta_{1i}(u_i, v_i)CropType_{ij} + \beta_{2i}(u_i, v_i)NumberofFrostFreeDays_{ij} + \beta_{3i}(u_i, v_i)SoilCompactionPercentage_{ij} + \in_i$
- Model C2:
  - $\widehat{Distance}_i = \beta_{0i}(u_i, v_i) + \beta_{1i}(u_i, v_i)CropType_{ij} + \beta_{2i}(u_i, v_i)NumberofFrostFreeDays_{ij} + \beta_{3i}(u_i, v_i)HydrologicGroup_{ij} + \in_i$

GAM:

- Generalized Additive Model Framework
  - Adds non-linear relationship between explanatory and response variables
    - Smooths predictors over regression splines
  - Non-linearity assumption caters for needs of spatial data!

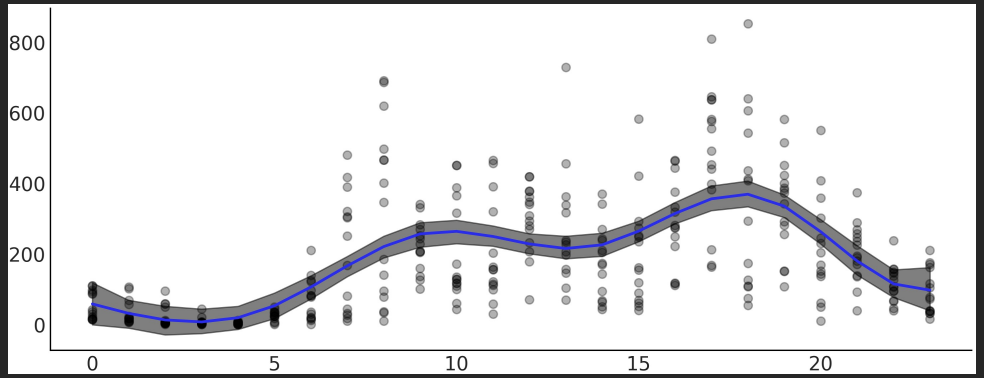


Image Source: Bayesian Computation Book

GAM:

- Use smoothing splines on Soil Compaction Percentage and Number of Frost-Free Days
- Model D1:
  - $\widehat{Distance}_i = \beta_0 + \beta_1 CropType_i + f_1(NumberofFrostFreeDays_i) + f_2(SoilCompactionPercentage_i) + \in_i$
- Model D2:
  - $\widehat{Distance}_i = \beta_0 + \beta_1 CropType_i + f_1(NumberofFrostFreeDays_i) + \beta_2 HydrologicGroup_i + \in_i$

Multinomial Model:

- Hazard class has multiple classes, thus lending its study to the multinomial framework
- Model B1:
  - $logit(Hazard\_Class_i) = \beta_0 + \beta_1 CropType_i + \beta_2 NumberofFrostFreeDays_i + \beta_3 SoilCompactionPercentage_i + \in_i$
- Model B2:
  - $logit(Hazard\_Class_i) = \beta_0 + \beta_1 CropType_i + \beta_2 NumberofFrostFreeDays_i + \beta_3 HydrologicGroup_i + \in_i$

Comparison Phase:

- Use AIC and BIC values as comparison metrics
- Further interpretations on superior models

Model	AIC	BIC
ModelA1	34912.11	34953.64
ModelA2	34849.41	34911.71
ModelB1	34625.07	34687.37
ModelB2	34599.70	34682.77
ModelC1	29603.25	23405.20
ModelC2	31888.16	25020.39
ModelD1	33914.79	33956.33
ModelD2	33933.46	33995.77
ModelE1	12433.80	12503.03
ModelE2	12660.46	12771.22

Results- ModelC1:

- GWR framework with Number of Frost-Free Days, Crop Type, and Soil Compaction Percentage as explanatory variables and Distance as response variable
- Conclusions: “Other” farms and pastureland are located further from wildfires
- Lack of practical importance

	Min.	1st Qu.	Median	Mean	3rd Qu.	Global
Intercept	-40.8	0.2	2.1	1.6	3.5	16.8
NumberOfFrostFreeDays	-0.1	0.0	0.0	0.0	0.0	0.2
CropTypeother	-15.6	-0.2	0.4	0.5	1.0	12.3
CropTypepasture	-21.6	-0.4	0.1	0.3	1.0	10.6
SoilCompactionPercentage	-0.1	0.0	0.0	0.0	0.0	0.1

Results- ModelE1:

- Multinomial framework with Soil Compaction Percentage, Crop Type and Number of Frost-Free Days as explanatory variables and Hazard Class as response variable
- Conclusions: Increased likelihood of lower severity classes for “Other” crops and pastureland

	X.Intercept.	SoilCompactionPercentage	CropTypeother	CropTypepasture	NumberOfFrostFreeDays
Moderate	0.8121657	1.005962	10.230472	3.1551053	0.9940749
Very High	1.5139184	1.024823	0.130852	0.7486428	0.9936610

Verification- ModelE1:

- Statistically significance: P-Values and Confidence Intervals
- Conclusion: Grapes are more vulnerable to wildfires!

	2.5 %.Moderate	97.5 %.Moderate	2.5 %.Very High	97.5 %.Very High
(Intercept)	0.6334215	1.0413495	1.1804901	1.9415231
SoilCompactionPercentage	1.0038475	1.0080803	1.0224606	1.0271911
CropTypeother	8.4576829	12.3748492	0.1044929	0.1638605
CropTypepasture	2.6484398	3.7586995	0.6494642	0.8629667
NumberOfFrostFreeDays	0.9931426	0.9950081	0.9926742	0.9946488

Conclusion:

- GWR with Distance as the response variable
  - Lack of practically meaningful results
- Multinomial with Hazard Class as the response variable
  - Evidence of grapes being located in more severe Hazard Classes
  - Implications: Grapes are more vulnerable to wildfires


Thank you!