Fire Vulnerability Mapping Process

The process to map fire vulnerability is similar to typical habitat niche modeling (Rotenberry 2006). As such, areas that are highlighted as vulnerable are defined as areas that have a similar range of environmental characteristics as compared to areas where a fire has been identified. The final raster is presented as percentages with each individual cell having a value between 0 and 100%. The value of an individual cell can be interpreted to be "the percentage similarity of this cell's environmental characteristics to a cell where a fire occurred."

1. Variable Selection

Following the guidelines of Weng, 2011 the environmental variables land use, elevation, slope, aspect, temperature, and population were used as predictor variables for presence of fire. The following table gives a summary of each dataset's relevant attributes. All data was resampled to 10m resolution for ease of analysis.

Variable	Data Origin	Resolution	Date	Data Type
Land use	NOAA C-Cap	10m	2005	Raster
Elevation	Saipan Lidar	10m	2007	Raster
Slope	Derived from Elevation	10m	2007	Raster
Aspect	Derived from Elevation	10m	2007	Raster
Temperature	WorldClim Model	10m	2020	Raster

2. Fire Locations

Historic Fires were mapped by Julian Dendy at the University of Hawaii using worldview satellite imagery. Their data encompasses fires throughout the island for the years of 2016-2019 inclusive. All fire data was handed over as polygons within an ESRI shapefile.

3. Modeling

The first step of the modeling process was to collect points of fire presence and absence. Using Arcpro's "Create Random Point" tool, 5000 points were created within the bounds of Julian's fire polygons representing points in which fire occurred. Another 5000 points were created using the same method but using a logic statement bounding the tool to where fires had not been identified. These 10,000 points were coded as 1's and 0's representing fire presence and fire absence. Arcpro's "Sample" tool was then used to sample each of the five environmental variables at each of these 10,000 points, and saved to an excel sheet.

From here the excel sheet was imported into Rstudio, a statistics software package. A Bayesian binomial regression was performed on this data, along with a stepwise AIC in order to identify the best performing model. As a result, slope, DEM and landcover were identified as significant variables in predicting fire occurrences. For landcover specifically, cover types; grasslands, scrub

shrub, open pasture, cultivated and evergreen were the most correlated to fire, with grasslands the most highly correlated.

The following table lists the model output for significant variables

Coefficients:				
	Estimate	Std. Error	Z value	Pr (>|z|)
Intercept	-3.084317	0.156816	-19.668	< 2e-16
Slope	0.054228	0.002889	18.773	< 2e-16
DEM	0.004334	0.000407	10.648	< 2e-16
Cover 6	2.613157	0.230486	11.338	< 2e-16
Cover 7	2.499953	0.357932	6.984	2.86e-12
Cover 8	4.524747	0.174436	25.939	< 2e-16
Cover 12	3.18495	0.166312	19.150	< 2e-16

In order to recover the probability, we exponentiate the log-odds coefficients with the following equation

$$Probability = \frac{e^{coefficents}}{1 + e^{coefficents}}$$

This equation is processed using the "Raster Calculator" in Arcpro.

This map can be used by stakeholders in inform on potential development risk, emergency response planning and environmental planning/research. Should questions arise on methods or data please reach out to the Coral Fellow Ilan Bubb at ibubb@dcrm.gov.mp