Habitat Suitability Models

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GSP 470

Geospatial Modeling

Introduction

Hyper Envelope Modeling Interface (HEMI) is a method of making Habitat Suitability Models using Bezier Curves to help with overfitting. By using Blue Spray, multiple covariates can be combined to make a potential habitat map. The statistics of Akaike Information Criterion (AIC) and Area Under Curve (AUC) are the primary statistics involved in understanding HEMI modeling results. The noise injection is used in a Monte Carlo loop to obtain a mean of statistics for several iterations. Jackknife technique is also utilized in comparing covariant statistics. Although HEMI is mainly used for Species habitat modeling, in this analysis, petroglyph archaeological sites location were used to create a potential habitat map. The goal of the study was to determine which habitat covariates played the highest role in the prediction map, and how noise and uncertainty play a role in interpreting the model results.

Methods

The habitat being modeled is that of ancient peoples of the northwest United States. Figure 1 shows the extent of the area with recorded native american rock art and settlements. Each of the sites have been selected to date 1000-10000 years old. The habitat layers selected for these sites were Solar Global Horizontal Irradiance, Temperature Range, Elevation, Aspect and precipitation. These raster layers were required to all have the same resolution and geographic extent in order to function properly in BlueSpray. All the layers were loaded into bluespray along with the point layer containing all the site locations. Using the wizard/HEMI 2 selection, all the data can be loaded and analyzed. Monte Carlo methods were utilized to analyze noise injection on covariants and create habitat maps. The statistics for each covariant were collected. Habitat and uncertainty maps were created. The response variable analyzed was the occurrence of ancient sites given the current environmental conditions.

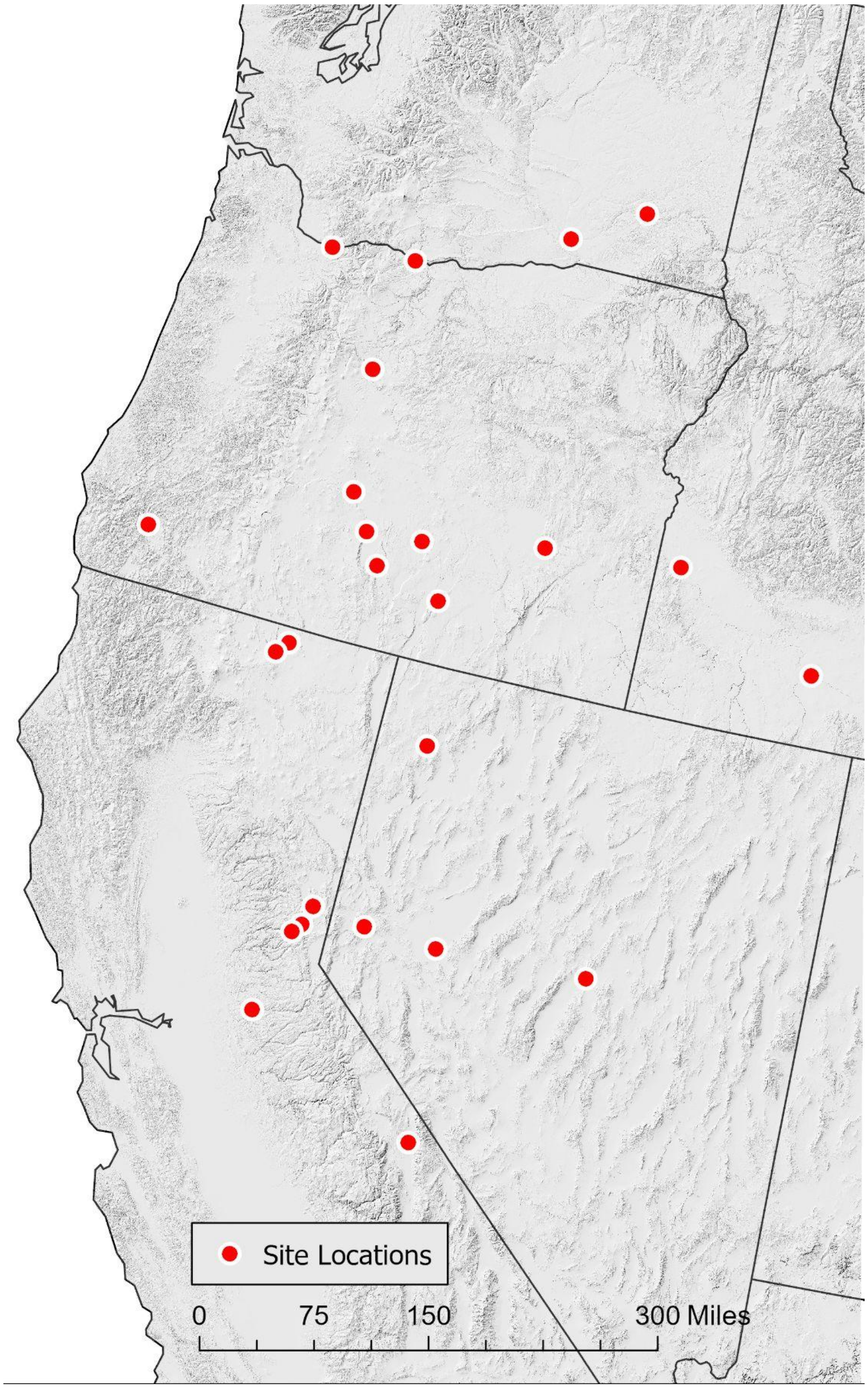

Figure 1: Study Area

Results

Figure 2 shows the HEMI dashboard with all covariants loaded and analyzed. The covariant with the highest AIC was Temperature Range. The worst AIC covariants were Precipitation and Aspect.

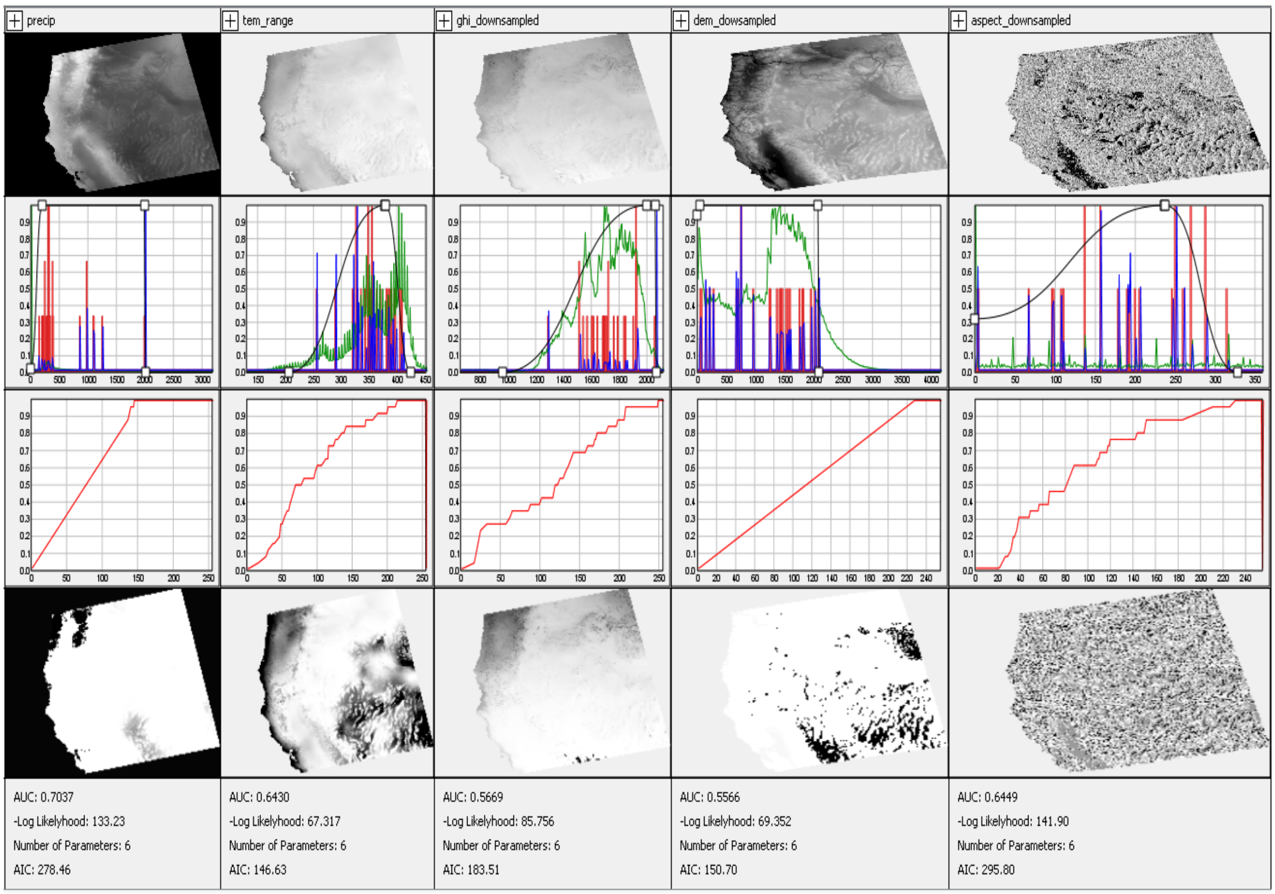

Figure 2: HEMI Dashboard with loaded covariants

The noise injection of the temperature range caused a variation in the results. The comparison of the standard results and the noise injected results can be seen in Figure 3. The Temperature range noise injected mean raster seems to have an increased amount of potential habitat, but the AUC is lower. Figure 4 shows the comparison of the uncertainty rasters. The noise injected model does have a significant amount more error than the original model.

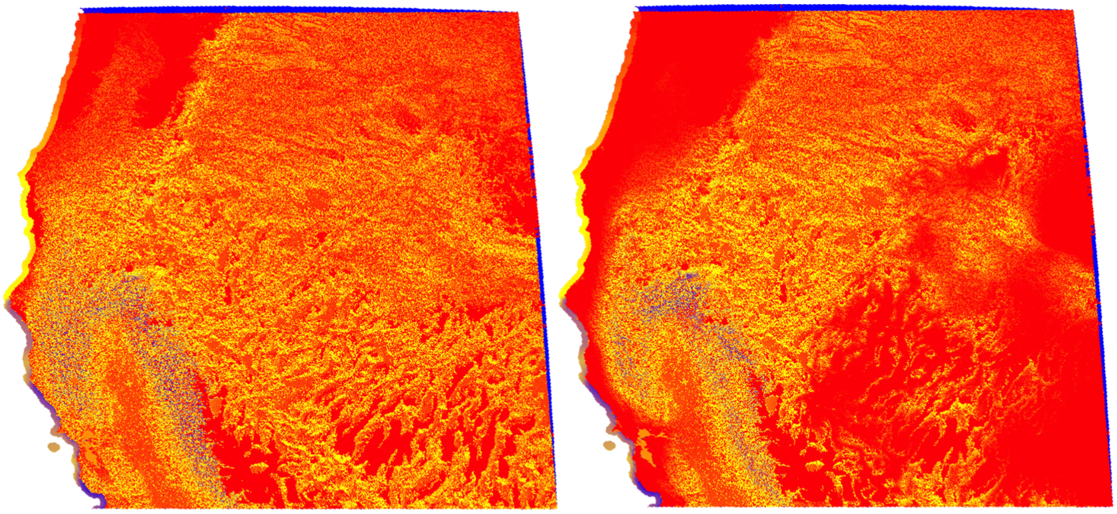

Figure 3: Prediction Map for Noise Injection Temp Range (left) & Regular Model

The uncertainty produced from the noise injection into the Temperature Range covariant can be seen in figure 4. The amount of error can be visually seen

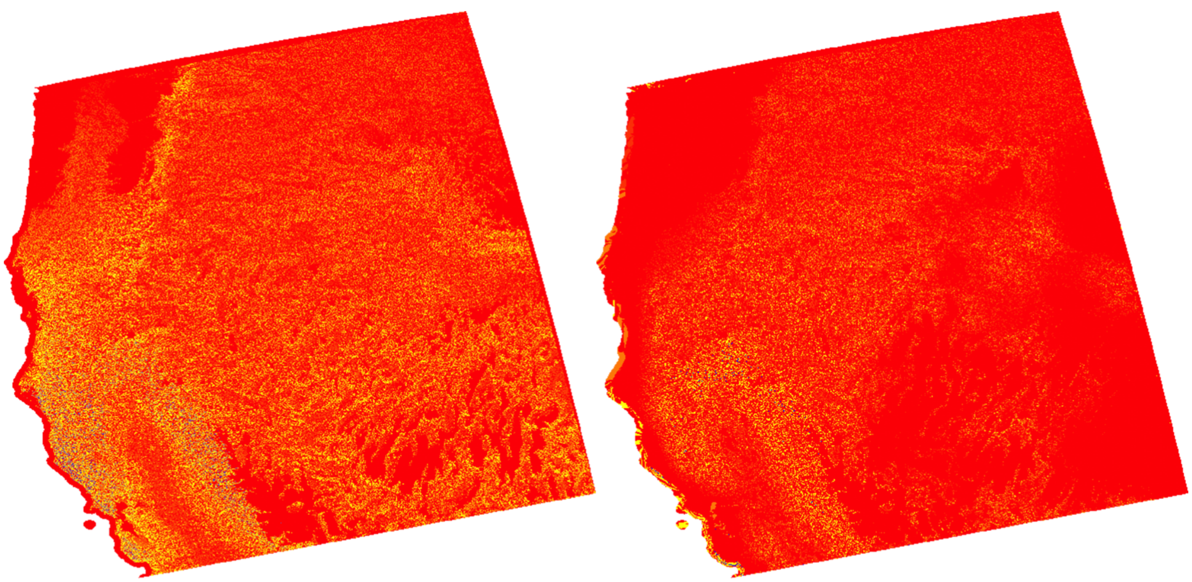

Figure 4: Uncertainty Map for Noise Injection Temp Range (left) & Regular Model

The model statistics were seen to get worse with the noise injection of the temperature range. Table 1 shows the output of model statistics. The noise injected had a higher AIC and a lower AUC; both negative indicators compared to the original model. Another important observation is that the weight of the Temp Range's AIC was significantly reduced with the noise injected.

Table 1: Temp Range Noise Injection & Regular Model Stats

8 Monte Carlo Iterations Regular						
Covariates	**Mean AIC**	**Std Dev AIC**	**Delta AIC**	**AIC Weight**	**Mean AUC**	**Std Dev AUC**
Temp Range	736	0	0	0.585	0.62465	0
Aspect	738	0	2	0.215	0.63193	0
DEM	741	0	5	0.079	0.51731	0
GHI	745	0	8	0.011	0.54455	0
Precip	745	0	9	0.011	0.40217	0
All	778	0	42	0.000	0.74215	0
8 Monte Carlo Iteration Noise Injection Temp Range						
Covariates	**Mean AIC**	**Std Dev AIC**	**Delta AIC**	**AIC Weight**	**Mean AUC**	**Std Dev AUC**
Aspect	738	0	0	0.389	0.63193	0
Precip	745	0	6	0.019	0.40217	0
Temp Range	739	5.69	0	0.389	0.54898	0.0409
GHI	745	0	6	0.019	0.54455	0
DEM	741	0	2	0.143	0.51731	0
All	779	5.68	41	0.000	0.71456	0.03101

Figure 5 displays the Habitat suitability map that was produced in HEMI, visualized in ArcGIS Pro. The symbology was classified to make the highest probability (red) contrast the other values. The model had a mean AIC of 778 and a AUC of about 74.2%

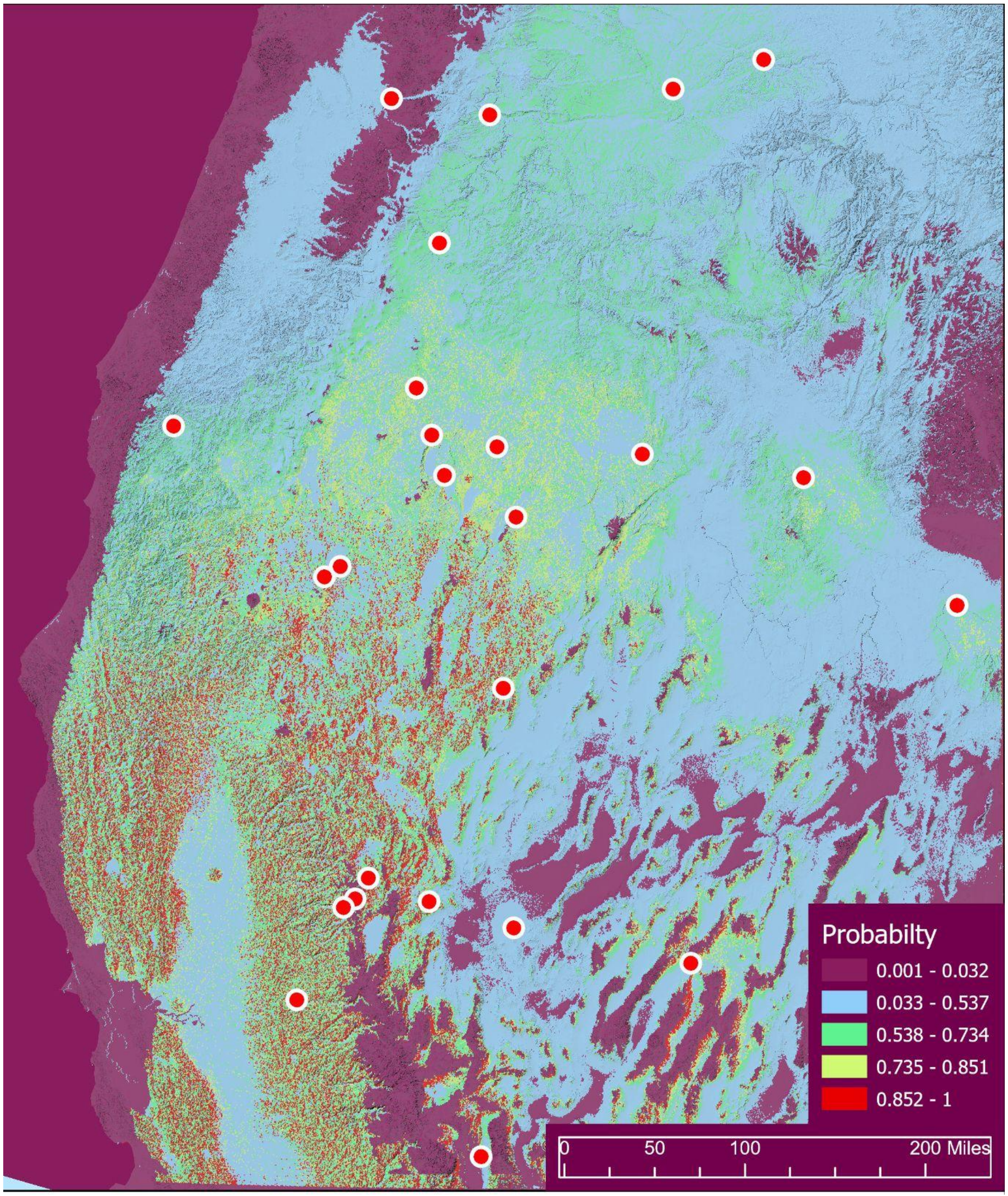

Figure 5: Habitat Suitability Map

Figure 6 shows the uncertainty map produced from HEMI visualized in ArcGISs Pro. from looking at the legend, the error is relatively low, however the pattern is quite dynamic.

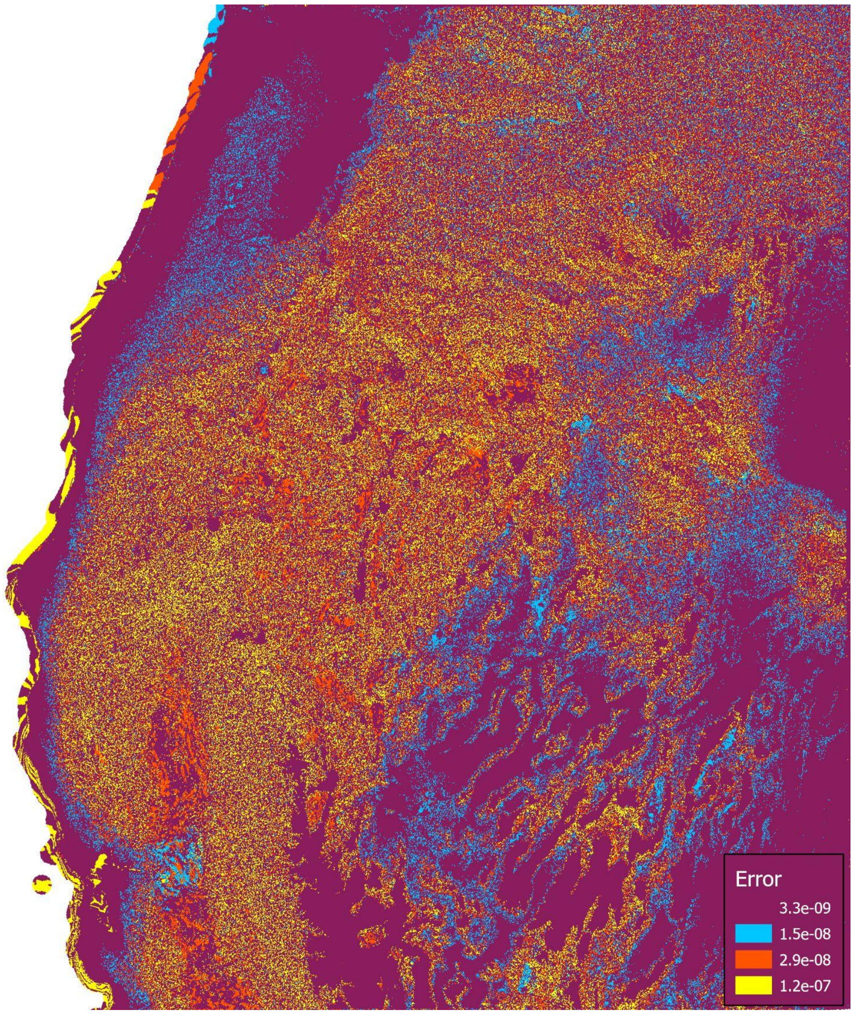

Figure 6: Map Of Uncertainty

Discussion/Conclusion

The HEMI wizard in BlueSpray produced a wide variety of analyses for the potential habitat of petroglyph locations. Although petroglyphs are not what HEMI was designed for, it can provide some insight into potential site locations. From figure 5 habitat map, the high probability areas become ambiguous in the mountain ranges surrounding the San Joaquin Valley, however in the Great Basin area and around Mt. Shasta has some isolated clusters. Therefore HEMI created some areas of interest that could provide a survey location for potential culturally sensitive structures. The adaption of habitat suitability to human activity is depending on some sort of trend in the selection of these sites. From looking at the covariants, the temperature range was a significant value. This can be due to many of the documented petroglyph locations being in desert areas, which have a higher temperature range due to lack of humidity. Aspect was the second most significant covariance. This indicates that the locations tend to be facing the same direction. By using a combination of the response curves, AIC, and AUC, the significance of covariates in a habitat can be better understood. The uncertainty map provided caution to areas of higher error. In this case, the error is higher in the areas of higher probability in the habitat map. This gives the future task of acquiring higher quality data in these areas. By repeating this analysis after higher quality data is acquired, an efficient workflow can be established to improve the models prediction capabilities.

Acknowledgements

Digital Elevation Model (DEM) Source: U.S. Geological Survey (USGS) Elevation Derivatives for National Applications (EDNA) [https://www.usgs.gov/core-science-systems/ngp/edna-elevation-derivatives-national-applications]

Global Horizontal Irradiance (GHI) Source: Global Solar Atlas [https://globalsolaratlas.info/]

Bioclimatic Temperature Range and Precipitation Data Source: NASA Earthdata [https://earthdata.nasa.gov/]