A brief introduction to Species Distribution Models in Python

Predicting spatial distributions for ecological species leveraging Python's ever-strengthening machine learning stack.

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Species Distributions Models (SDMs) are an important and widely used tool for ecologists, agriculture scientists, conservation biologists, and many other geospatial science enthusiasts. While dozens of tutorials leverage the traditional R stack for SDMs, with packages such as Raster, implementations of SDMs in Python are, ***surprisingly***, rather limited. To bridge this gap, we explore a SDM workflow powered by Python's machine learning capabilities. The methods employed barely scratch the surface of available techniques, and hopefully this introduction can serve as a springboard to further exploration.

If you are completely new to SDMs, it may be prudent to start here (https://www.google.com/search?q=species+distribution+modeling&oq=species+distribution+modeling&aqs=chrome..69i57j35i39j0l3j69i61l2j69i60.6 8). SDMs associate presence locations of a species to climate variables, giving you the power to predict species suitability across an entire landscape. First, environmental variables are sampled from presence coordinates. Second, a statistical model (here, SK-Learn classifiers) defines a species-environment relationship. Third, the species–environment relationship is mapped across the study space, denoting a potential distribution of the species (referred to as interpolation). Projecting to future/past climates or to novel geographic areas is referred to as extrapolation. A typical workflow is as follows:

```
conceptualization -> data pre-processing -> model training/assessment ->
interpolate/extrapolate -> iterate
```

Tutorial Objectives

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1. Create a SDM workspace with a Python codebase.
2. Run a suite of SDMs with your ML classifiers of choice.
3. Visualize model predictions with climate features (1970-2000).

Section 1 | Set up

1.1 | Workspace

The first step is to create `inputs` / `outputs` folders in our working file directory. It is best practices to keep the data and results separated, as `outputs` folder should be completely reproducible.

In [1]:
```
import os
os.mkdir("inputs")
os.mkdir("outputs")
```

We now install the additional dependencies we will need for our SDMs, with four primary libraries:

- ***scikit-learn***: De-facto Python machine learning
- ***pyimpute***: spatial classification
- ***rasterio***: reads and writes geospatial rasters
- ***geopandas***: spatial operations in Python made easy

These can be installed at the terminal using `pip install LIBRARY` , but you may find it cleaner to create a conda virtual environment from `requirements-py.txt` (see Git repo (https://github.com/daniel-furman/py-sdms-tutorial)).

1.2 | Data Processing

We first need to download a geodatabase (here we use a `.shp` file) denoting presence/absence coordinates, which can be directly loaded into Python as a GeoPandas `GeoDataFrame` (a tabular data structure for geometric data types). Here, the `CLASS` column is a binary indication of the presence/absence of the species. For this tutorial, we are using Joshua trees (*Yucca brevifolia*) as the example species:

To follow along chunk by chunk, clone the [Git repo (https://github.com/daniel-furman/py-sdms-tutorial)](https://github.com/daniel-furman/py-sdms-tutorial) and open `Intro-to-SDMs-Py.ipynb` in your working directory of choice.

In [2]:

```
import geopandas as gpd
import shutil
import glob
# grab jtree data after cloning Git repo
for f in sorted(glob.glob('data/jtree*')):
    shutil.copy(f,'inputs/')
# or grab your data of choice and move to 'inputs/'
pa = gpd.GeoDataFrame.from_file("inputs/jtree.shp")
pa.sample(5) # GeoDataFrame for the species
```

Out[2]:

	CLASS	geometry
244	0.0	POINT (-111.81250 34.52083)
5211	1.0	POINT (-116.14671 34.02692)
3552	1.0	POINT (-113.18179 34.36595)
3230	1.0	POINT (-115.71752 36.44939)
3387	0.0	POINT (-113.89583 35.85417)

We now check that there are no duplicate or `NaN` coordinates, as well as inspect the shapefile's attributes.

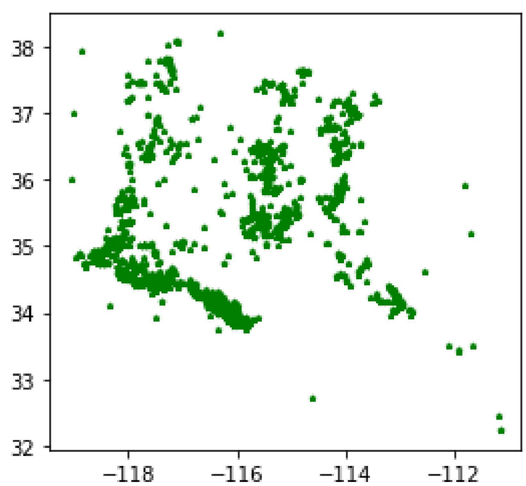
In [3]:
```
print("number of duplicates: ", pa.duplicated(subset='geometry', keep='first').sum())
print("number of NA's: ", pa['geometry'].isna().sum())
print("Coordinate reference system is: {}".format(pa.crs))
print("{} observations with {} columns".format(*pa.shape))
```

```
number of duplicates:  0
number of NA's:  0
Coordinate reference system is: epsg:4326
7200 observations with 2 columns
```

We can map the species presences (`pa==1`).

In [4]:
```
pa[pa.CLASS == 1].plot(marker='*', color='green', markersize=8)
```

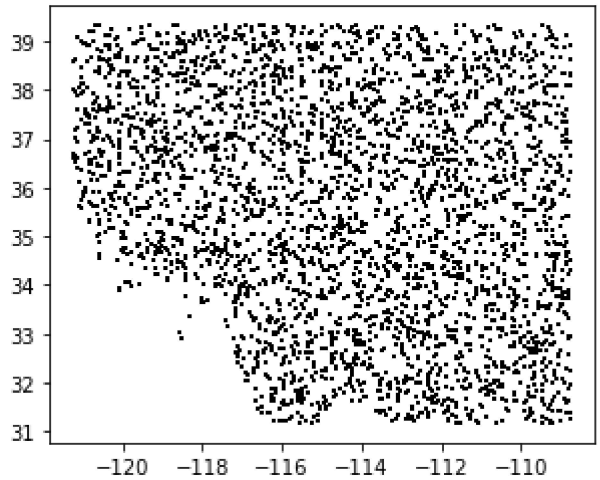
Out[4]: `<AxesSubplot:>`



And we can map the background points (`pa == 0`).

In [5]:
```
pa[pa.CLASS == 0].plot(marker='+', color='black', markersize=4)
```

Out[5]: <AxesSubplot:>



However, if you don't have a geospatial database with presences/absence coordinates, there are some easy steps to create one for ***virtually any species*** of interest! You can start by searching the open-data Global Biodiversity Information Facility (GBIF (https://www.gbif.org)), downloading a species database to `.csv` , and migrating to R to pipe the database to `.shp` (e.g. see `data-pre-processing.R` in the Git repo (https://github.com/daniel-furman/py-sdms-tutorial) or the additional information section below).

Section 2 | Mapping species suitability

In this section we will train our machine learning classifiers and make spatial predictions of the species distribution over current conditions (1970-2000).

First, we load 19 bioclimatic features (here we use 2.5 arc-minute resolution) from the publicly available WorldClim database (https://www.worldclim.org) (v. 2.1, Fick & Hijmans, 2017).

In [6]:
```
# grab climate features - cropped to joshua tree study area
for f in sorted(glob.glob('data/bioclim/bclim*.asc')):
    shutil.copy(f,'inputs/')
raster_features = sorted(glob.glob(
    'inputs/bclim*.asc'))
# check number of features
print('\nThere are', len(raster_features), 'raster features.')
```

```
There are 19 raster features.
```

We are now ready to use `pyimpute` to generate the raster maps of suitability. We first prep the pyimpute workflow:

In [7]:
```
from pyimpute import load_training_vector
from pyimpute import load_targets
train_xs, train_y = load_training_vector(pa, raster_features, response_field
='CLASS')
target_xs, raster_info = load_targets(raster_features)
train_xs.shape, train_y.shape # check shape, does it match the size above of t
he observations?
```

Out[7]:
```
((7200, 19), (7200,))
```

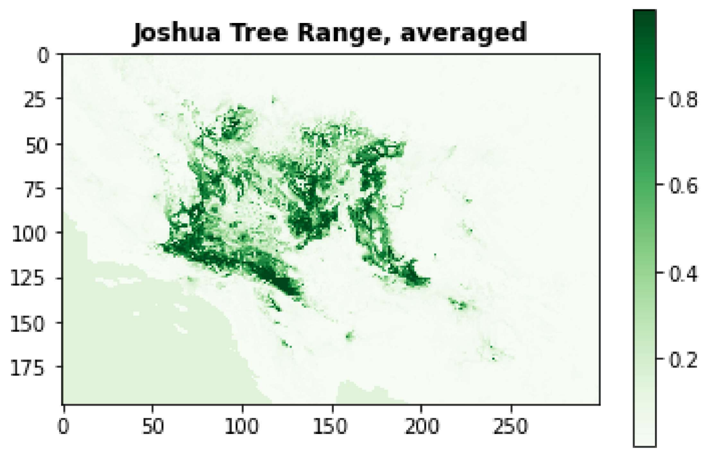
and we implemement several `scikit-learn` classifiers:

In [8]:
```
# import machine learning classifiers
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import ExtraTreesClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier

CLASS_MAP = {
    'rf': (RandomForestClassifier()),
    'et': (ExtraTreesClassifier()),
    'xgb': (XGBClassifier()),
    'lgbm': (LGBMClassifier())
    }

from pyimpute import impute
from sklearn import model_selection
# model fitting and spatial range prediction
for name, (model) in CLASS_MAP.items():
    # cross validation for accuracy scores (displayed as a percentage)
    k = 5 # k-fold
    kf = model_selection.KFold(n_splits=k)
    accuracy_scores = model_selection.cross_val_score(model, train_xs, train_
y, cv=kf, scoring='accuracy')
    print(name + " %d-fold Cross Validation Accuracy: %0.2f (+/- %0.2f)"
          % (k, accuracy_scores.mean() * 100, accuracy_scores.std() * 200))

    # spatial prediction
    model.fit(train_xs, train_y)
    os.mkdir('outputs/' + name + '-images')
    impute(target_xs, model, raster_info, outdir='outputs/' + name + '-image
s',
           class_prob=True, certainty=True)
```

```
rf 5-fold Cross Validation Accuracy: 93.67 (+/- 0.54)
et 5-fold Cross Validation Accuracy: 93.82 (+/- 0.99)
xgb 5-fold Cross Validation Accuracy: 93.54 (+/- 0.99)
lgbm 5-fold Cross Validation Accuracy: 93.67 (+/- 0.88)
```

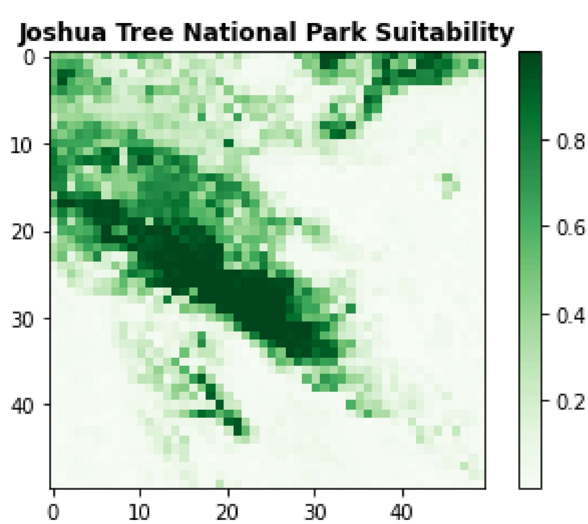
All done! We have a `responses.tif` raster which is the predicted class (0 or 1) and `probability_1.tif` with a continuous suitability scale. Let's average the continuous output for the four models and plot our map.

In [9]:
```
from pylab import plt
# define spatial plotter
def plotit(x, title, cmap="Blues"):
    plt.imshow(x, cmap=cmap, interpolation='nearest')
    plt.colorbar()
    plt.title(title, fontweight = 'bold')

import rasterio
distr_rf = rasterio.open("outputs/rf-images/probability_1.0.tif").read(1)
distr_et = rasterio.open("outputs/et-images/probability_1.0.tif").read(1)
distr_xgb =  rasterio.open("outputs/xgb-images/probability_1.0.tif").read(1)
distr_lgbm =  rasterio.open("outputs/lgbm-images/probability_1.0.tif").read(1)
distr_averaged = (distr_rf + distr_et + distr_xgb + distr_lgbm)/4

plotit(distr_averaged, "Joshua Tree Range, averaged", cmap="Greens")
```



Lastly, let's zoom in to Joshua Tree National Park and inspect the suitability there.

In [10]:
```
plotit(distr_averaged[100:150, 100:150], "Joshua Tree National Park Suitabilit
y", cmap="Greens")
```



Additional resources

1. Species distribution modeling with R (https://cran.r-project.org/web/packages/dismo/vignettes/sdm.pdf) (Hijmans and Elith, 2017)
2. Pyimpute's README.md (https://github.com/perrygeo/pyimpute/blob/master/README.md)
3. A study on generating pseudo absence points (https://www.researchgate.net/publication/229149956_Selecting_Pseudo-Absences_for_Species_Distribution_Models_How_Where_and_How_Many) (Barbet-Massin et al., 2012)
4. A study on SDM transferability and pixel size (https://www.nature.com/articles/s41598-018-25437-1) (Manzoor et al., 2018)
5. A study on SDMs for invasive species (https://onlinelibrary.wiley.com/doi/full/10.1111/ddi.13161) (Lake et al., 2020)
6. A book on mapping SDMs (https://www.amazon.com/Mapping-Species-Distributions-Biodiversity-Conservation/dp/0521700027) (Franklin, 2009)
7. A more modern SDMs tutorial (https://damariszurell.github.io/SDM-Intro/) (Zurell, 2020)
8. A study on collinearity among model variables (https://onlinelibrary.wiley.com/doi/full/10.1111/j.1600-0587.2012.07348.x) (C. F. Dormann et al., 2012)

Data Citations

1. GBIF.org (01 November 2020) GBIF Occurrence' Download https://doi.org/10.15468/dl.g6swrm (https://doi.org/10.15468/dl.g6swrm)
2. Fick, S.E. and R.J. Hijmans, 2017. WorldClim 2: new 1km spatial resolution climate surfaces for global land areas. International Journal of Climatology 37 (12): 4302-4315.