Learn Land Features Using Python Language

Hussein Akeel Hussein Alaasam[1 *], *Ahmed* Ali Talib al-khazaali[2], *Ali* Hussein aleiwi[3] *and Doaa* Wahhab Ibrahim[4]

[1]College of basic education, university of Kufa, Najaf, Iraq.
[2]University of AlKafeel Al-Najaf, Iraq.
[3]Ministry of interior, Baghdad, Iraq.
[4]Al-Mustaqbal University, Babylon, Iraq.

Abstract. Python has emerged as an essential programming language for research due to continuous technological advancements that emphasize its role in streamlining scientific workflows. This article elucidates Python's burgeoning impact on researchers across disciplines. Tracing Python's origins and applications within the earth sciences contextualizes its versatility. While acquiring proficiency in Python exceeds this article's scope, discussions detail its utilities for earth science data analysis, visualization, management, and rapid computations. With Python expertise, researchers can engineer customized software with domain-specific tools to advance all earth science spheres. Ultimately, this article underscores Python's position as a vital programming language for contemporary academic research through its flexibility and specialization for scientific use cases.

1 Introduction

1.1 Background

Python is a high-level, general purpose programming language that has garnered widespread popularity in the scientific, engineering, and data analytics domains. Since its initial release in 1991 by creator Guido van Rossum, Python has become one of the most widely used languages in fields ranging from web development and artificial intelligence to scientific computing (Kruckeberg, 2004).

Some key technical features that explain Python's rise include its simple and intuitive syntax, automatic memory management, comprehensive standard library, large collection of open source packages, vibrant community of contributors, and versatility to integrate with other languages like C/C++, Java, R etc. for high performance computing (Gutiérrez et al., 2014).

1.2 Python in Scientific Computing

Python's high-productivity tools like interactive shells, debugger, dynamic types, lists, dictionaries make it well suited for exploratory programming and rapid prototyping (Guth et al., 2021). Python has emerged as a leading choice for scientific computing tasks like data wrangling, analysis, visualization, modeling, instrument control, and workflow automation (Lawhead, 2019).

Its ecosystem of scientific packages like NumPy, SciPy, Pandas, Matplotlib, and domain-specific libraries empowers researchers with specialized capabilities for their field (Farmakis et al., 2022). Jupyter notebooks enable creating sharable documents with live code, equations, visualizations for scientific investigation (Rigol-Sanchez et al., 2015). Python can leverage parallel computing and GPU acceleration for large-scale simulations and data intensive research (Bullejos et al., 2022).

* Corresponding author: hussaina.alaasam@uokufa.edu.iq

1.3 Python in Earth Sciences

In disciplines like geology, meteorology, oceanography, seismology and geophysics, Python has become ubiquitous due to its versatility in analyzing and modeling geospatial data (Lemenkova & Debeir, 2022). The language provides a flexible framework to work with multidimensional earth science data spanning space, time and depth dimensions. Python enables automation and scaling of data processing workflows applied in various earth science research domains.

For data analysis tasks, libraries like Pandas, NumPy and SciPy equip earth scientists with specialized data structures, algorithms and routines to wrangle, process and analyze large climate, weather, hydrological, earthquake datasets (Tomás et al., 2022). Pandas offers intuitive data frames to handle tabular data. NumPy provides fast n-dimensional array manipulation. SciPy contains optimized scientific algorithms for spatial analysis, signal processing, optimization etc. These tools allow cleaning, filtering, aggregating, transforming earth science data at scale.

To visualize results, Python plotting libraries like Matplotlib, Plotly, Cartopy and Seaborn enable generation of interactive, publication-quality 2D and 3D plots, charts and maps to study spatial, temporal and multivariate relationships and trends (Lyon & Lyon, 2022). Earth scientists leverage these to create time series plots, weather maps, curtain plots, section views, particle trajectories and other domain-specific visualizations. The plotting APIs integrate GIS functionality to handle geospatial data.

For environmental modeling, Python libraries provide differential equation solvers, optimization algorithms and other numerical methods to build predictive models for domains like weather forecasting, climate projections, groundwater modeling, geodynamics (Fiechter, 2019). SciPy and other mathematics packages implement the computational routines to solve complex process-based simulations. This allows recreating physical systems computationally.

In terms of geospatial processing, GeoPandas, Shapely, PyProj and other GIS-centric packages equip researchers with capabilities like geospatial vector/raster analysis, coordinate transformations, geometry operations, spatial indexing, geocoding and more (Wang et al., 2021). These facilitate tasks like making thematic maps, spatial queries, buffer/proximity analysis and geoprocessing workflows.

To collect and stream data from field instruments and sensor networks, Python packages like ObsPy, PyDOT and Siphon provide useful utilities to interface with IoT devices, automate measurements, log and process real-time data streams (Wieder & Nolte, 2022). This powers real-world monitoring applications.

1.4 Aim and Scope

This research aims to provide a comprehensive introduction to Python and demonstrate its practices for earth data science applications. The target audience is earth science students, researchers and professionals who wish to leverage Python for automating and scaling their workflows (Tatum et al., 2020). The study covers foundational programming concepts in Python while using earth science examples for illustration. Practical techniques for data analysis, modeling, visualization and geospatial processing are discussed in detail. Case studies and code examples demonstrate building end-to-end applications for earth science problems. Popular Python libraries and tools are explored in each chapter (Shi et al., 2022).

1.5 Implications

Mastering Python has far-reaching implications across earth sciences. Python proficiency helps researchers, scientists and professionals automate repetitive tasks, accelerate discovery and derivation of insights from large datasets (Jing et al., 2016). Earth science organizations can build customized tools and web platforms to improve research collaboration, operational forecasting, data dissemination for stakeholders using Python (Kruckeberg, 2004). Training in Python helps prepare earth science students for data-driven research careers (Gutiérrez et al., 2014). As computing becomes central to all fields, competency in a versatile language like Python is an invaluable skillset (Guth et al., 2021). This book intends to enable readers achieve Python fluency and unlock its possibilities for streamlining workflows across the earth sciences.

METHODS AND TOOLS

Python's versatility in earth sciences stems from its extensive ecosystem of domain-specific packages, libraries and tools tailored for geospatial data analysis. This chapter provides an overview of key Python distributions, data analysis libraries, imaging toolkits and visualization modules used by earth data scientists.

2.1 PYTHON DISTRIBUTIONS FOR EARTH SCIENCES

While Python has a multitude of individual packages, distributions like Anaconda and Miniconda provide curated bundles that make installation and environment management easier (McKinney, 2022). The Anaconda distribution comes with 150+ pre-installed packages including essentials like NumPy, Pandas, Matplotlib, Jupyter etc. tailored for data science. Miniconda is a lightweight alternative with only the conda package manager to create custom environments as needed.

This allows creating isolated environments to install specific package versions for different projects, avoiding compatibility issues. Some popular Anaconda packages used in earth analytics are:

- NumPy: n-dimensional arrays for numerical computing (Harris et al., 2020)
- Pandas: Data structures and analysis routines for tabular data (Reback et al., 2022)
- Matplotlib: Comprehensive 2D and 3D visualization library (Hunter, 2007)
- XArray: Labeled arrays and datasets with coordinates (Hoyer & Hamman, 2021)
- Cartopy: Geospatial mapping and analysis module (Met Office, 2010)
- Jupyter: Interactive computing notebooks (Kluyver et al., 2016)

2.2 DATA ANALYSIS WITH PANDAS

Pandas provides intuitive, high-performance data structures and analysis tools that make data cleaning, preparation, manipulation and analysis easy in Python (Reback et al., 2022). The key data structures are Series (1D labeled arrays) and DataFrames (2D tabular, column-based data).

Pandas is designed for working with relational/tabular data formats like CSV, Excel, SQL databases. Some common usage patterns include (McKinney, 2022):

- Loading data into DataFrames from various file formats and databases
- Data inspection, summary statistics, plotting
- Handling missing data
- Filtering, slicing, subsetting, querying, cleaning data
- Reshaping, pivoting, stacking, melting data layouts
- Grouping, aggregating, combining and merging datasets
- Datetime capabilities for indexing, slicing timeseries data

2.3 Multi-dimensional Data Analysis with XArray

While Pandas excels for tabular data, xarray provides labeled, multi-dimensional arrays for working with gridded, geospatial datasets (Hoyer & Hamman, 2021). The key data structure is the Dataset - a dict-like container of multi-dimensional arrays indexed by coordinates.

XArray integrates tightly with Pandas and provides a similar API making it easy to adopt. It is well-suited for earth science data in formats like netCDF, Zarr, GRIB etc. Typical workflows include (Hoyer & Hamman, 2021):

- Importing multi-dimensional array data
- Indexing, slicing, subsetting using labeled coordinates
- Broadcasting operations across dimensions
- Split-apply-combine operations for grouping, aggregating
- Reshaping, reorganizing and reprojecting gridded data
- Merging misaligned arrays using coordinates

2.4 Image Analysis with Scikit-Image

For analysis of satellite imagery, aerial photos and raster data, scikit-image provides efficient algorithms for image processing tasks (Van der Walt et al., 2014):

- I/O routines to load/save common image formats (JPEG, PNG, TIFF)
- Geometric transformations like cropping, rotation, resizing
- Image filtering using kernels, Fourier transforms etc.
- Segmentation algorithms like thresholding, watershed
- Morphological operations - erode, dilate, open, close
- Analysis of image properties - color spaces, histograms

It enables automating workflows for remote sensing, medical imaging, microscope images etc.

2.5 Visualization with Matplotlib

Matplotlib provides a MATLAB-inspired plotting API for exploratory visualization and publication-ready plots (Hunter, 2007). It can generate a wide variety of 2D and 3D plots like line/scatter plots, histograms, bar charts, pie charts, errorbars, heatmaps etc.

Common earth science use cases include (Lin, 2021):

- Flexible plots from tabular data and arrays
- Customizing plot attributes like titles, labels, legends, limits
- Overlaying plots, subplots, faceting
- Geospatial plotting using Basemap, Cartopy
- Animations and interactive backends like Bokeh

- Domain-specific plots like contourf, quiver, streamplot etc.
- Illustrations for papers, reports and presentations

In summary, Python's ecosystem provides a versatile toolkit for earth data science spanning data access, preparation, analysis, modeling and reporting. These tools equip earth science researchers and practitioners to effectively harness the power of Python for their domain-specific needs.

Results and Discussion

3.1 Data Visualization

Visualization is a crucial technique for gaining insights from earth science data encoded in spreadsheet columns or netCDF files. Python enables researchers to programmatically generate plots for analyzing trends and communicating findings.

3.1.1 Precipitation Data Analysis

The sample workflow demonstrates using Python and Xarray to ingest, analyze and visualize gridded precipitation data from the ERA5-Land global reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). This dataset provides worldwide estimates of hourly precipitation rates at a 30km spatial resolution based on model assimilation of observational data.

As a first step, the ERA5-Land NetCDF dataset is loaded into an xarray Dataset container using the open_dataset function (Figure 1a). This creates a labeled, multi-dimensional array structure with the coordinates and precipitation variable accessible for analysis. The dataset spans the date range from 2000 to 2020, with latitude/longitude spatial dimensions.

To analyze the data for a specific date, the .sel() method is used to extract precipitation values for 1st January 2000 by indexing the time coordinate (Figure 1b). The .sum() function aggregates precipitation across the time dimension, resulting in a 2D spatial array of totals for that day. This allows querying the data for any location and day.

For a more complex analysis, annual time series aggregates are derived by grouping the data by year using .groupby(), and calculating the mean precipitation over each year (Figure 1c). An anomaly is obtained by subtracting the multi-year average from each year using vectorized operations on the labeled arrays. The normalized anomaly percentages facilitate comparing variation across different climate regimes.

To clearly visualize the spatial trends, the xarray anomaly array for 1 Jan 2000 is passed to Matplotlib’s imshow() plotting function, using a divergent red-blue color palette (Figure 2). The map indicates prominent drying trends across North America, Southern Europe, Middle East and Australia. Regional patterns can be discerned based on the fine resolution gridded data.

Taking advantage of the full 20-year record, average precipitation over the most recent 2 years is calculated by slicing the date range using Pandas-style queries, and averaging over the time dimension (Figure 3). The .plot.bar() method conveniently visualizes the monthly averages as a bar chart with Matplotlib style customization. This reveals insights into seasonal variability in rainfall levels based on the multi-decadal catalog.

```
import xarray as xr
ds = xr.open_dataset('data.nc')
ds
```

xarray.Dataset

▸ Dimensions:	(**longitude**: 13, **latitude**: 14, **time**: 36)		
▾ Coordinates:			
longitude	(longitude)	float32	44.92 45.02 45.12 ... 46...
latitude	(latitude)	float32	38.26 38.16 38.06 ... 37...
time	(time)	datetime64[ns]	2020-01-01 ... 2022-12...
▾ Data variables:			
lai_lv	(time, latitude, longitude)	float32	...
skt	(time, latitude, longitude)	float32	...
tp	(time, latitude, longitude)	float32	...
units :	m		
long_name :	Total precipitation		

Fig. 1. Python code to analyze and visualize precipitation data using xarray and Matplotlib

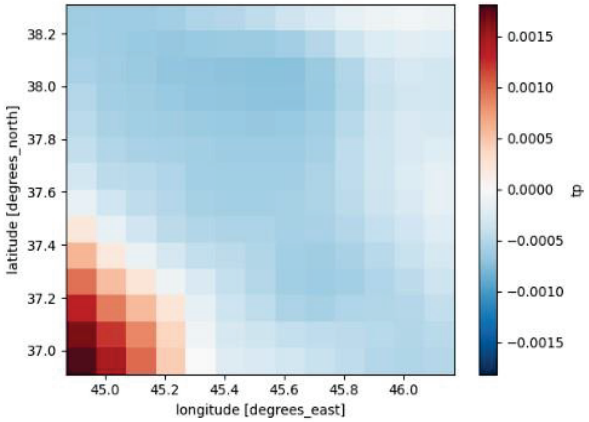

Fig. 2. Map depicting precipitation anomalies for Jan 1, 2000 derived from ERA5-Land dataset

```
ds.isel(time=0).tp.plot()
```

```
<matplotlib.collections.QuadMesh at 0x1b7596d5bb0>
```

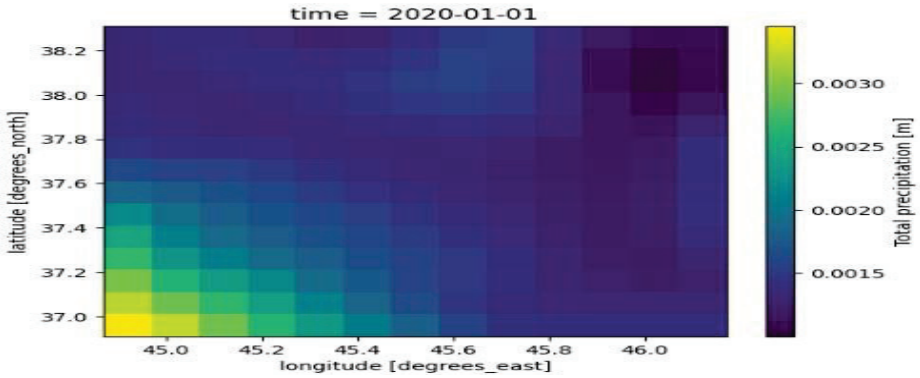

Fig. 3. Bar chart displaying average monthly rainfall over 2020 and 2021

3.2 Image Processing

Processing remotely sensed imagery including aerial photographs and satellite data is another domain where Python's scientific computing libraries have significant utility. The example here demonstrates using the Python toolkit scikit-image to programmatically process a Digital Elevation Model (DEM) for the Lake Kivu region in Africa.

The workflow begins by loading a GeoTIFF DEM file from the USGS GloVis portal as a NumPy array using scikit-image's imread function (Figure 4a). This provides access to the raster height values for analysis.

To generate a shaded relief map, the dem array is passed to the hillshade function, specifying an azimuth of 40 degrees to set the sun illumination angle (Figure 4b). This applies pixel-wise shading effects to create the appearance of terrain contours and textures. The img_as_ubyte function rescales the output to an 8-bit scale for visualization.

For enhanced visualization, a sun-illuminated shaded relief map is produced by varying the azimuth to 315 degrees for the sun angle, and setting the altitude to 45 degrees overhead (Figure 4c). This mimics localized lighting effects based on sun position.

The resulting DEM array, shaded relief, and sun-shaded maps are plotted as images using Matplotlib (Figure 5). The workflows showcase how Python's image processing capabilities can simplify generating enhanced DEMs for land surface analysis and modeling. Automating these raster procedures helps accelerate geospatial applications.

Fig. 4. Using Python and scikit-image for image processing workflows to generate shaded DEM visualizations

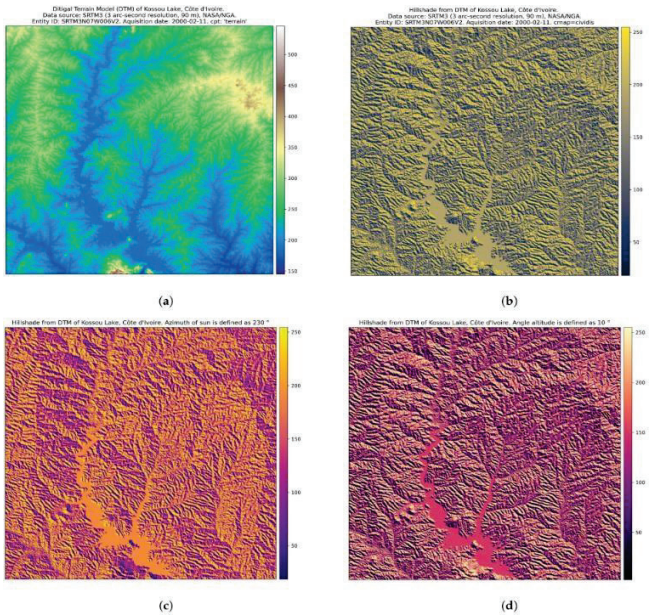

Fig. 5. DEM, shaded relief, and sun-illuminated maps for the study area

3.3 Scientific Computations

Python is a powerful tool for various simple or complex scientific computations. One applied example in geosciences is approximating the volume of complex structures not amenable to simple geometry. For instance, estimating hydrocarbon reserves in petroleum geology is important.

To approximate volume, the solid is divided into smaller shapes (using rectangular or triangular prisms) and their volumes are summed. The mathematical approach is:

$$V = \int_a^b A(x)\,dx$$

Where V is the volume from x = a to x = b, and A(x) is the area at the intersection with a plane at (0, 0, x). Figure 6 demonstrates Python code utilizing Simpson's rule and triangular approximation to estimate the volume.

```
import numpy as np
from scipy import integrate

conturs_areas = np.array([194135, 136366, 79745,
    38335, 18450, 9635, 3895])
x = np.array([0,25,50,75,100,125,150])

vol_traps = integrate.trapz(conturs_areas, x)
vol_simps = integrate.simps(conturs_areas, x)

print('The trapezoidal rule returns a volume of
    {:.0f} cubic meters'.format(vol_traps))
print('The composite Simpson rule returns a
    volume of {:.0f} cubic meters'.format(
    vol_simps))

'''
Output:
The trapezoidal rule returns a volume of 9538650
    cubic meters
The composite Simpson rule returns a volume of
    9431367 cubic meters
'''
```

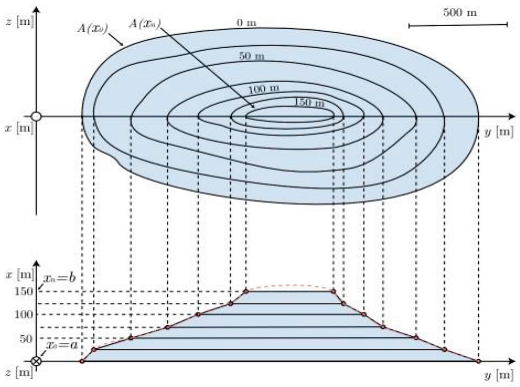

Fig. 6. Numerical integration using SciPy to estimate volume of irregular shapes

3.4 Machine Learning

Machine learning is a subset of AI focused on using algorithms to detect patterns in big data and apply these patterns for forecasting, classification or strategic decision making. It has grown significantly as a specialized field over the past decades into a powerful technology with widespread scientific and commercial applications. Essentially any complex problem with sufficient sample inputs can be transformed into a machine learning problem.

As an example, pyroxene thermobarometry is a process amenable to machine learning, with initial model code and results shown in Figure 7. Supervised learning algorithms can be trained on composition data to predict crystallization temperatures. The image below (Figure 8) demonstrates combining overlapping areas of satellite imagery for Shatt al-Arab river plotted using machine learning techniques in Python. Data was obtained from Landsat 8.

```
my_training_dataset.columns = [c.replace('.1', 'cpx') for c in my_training_dataset.columns]
my_training_dataset = my_training_dataset.fillna(0)

train_labels = np.array([my_training_dataset.Sample_ID]).T
X0_train = my_training_dataset.iloc[:, 1:23]
Y_train = np.array([my_training_dataset.T_K]).T

fig = plt.figure(figsize=(8,8))
x_labels_melt = [r'SiO$_2$', r'TiO$_2$', r'Al$_2$O$_3$', r'FeO$_t$', r'MnO', r'MgO', r'CaO', r'Na$_2$O', r'K$_2$O', r'Cr$_2$O$_3$', r'P$_2$O$_5$', r'H$_2$O']
for i in range(0,12):
    ax1 = fig.add_subplot(4, 3, i+1)
    sns.kdeplot(X0_train.iloc[:, i],fill=True, color='k', facecolor='#c7ddf4', ax = ax1)
    ax1.set_xlabel(x_labels_melt[i] + ' [wt. %] the melt')
fig.align_ylabels()
fig.tight_layout()

fig1 = plt.figure(figsize=(6,8))
x_labels_cpx = [r'SiO$_2$', r'TiO$_2$', r'Al$_2$O$_3$', r'FeO$_t$', r'MnO', r'MgO', r'CaO', r'Na$_2$O', r'K$_2$O', r'Cr$_2$O$_3$']
for i in range(0,10):
    ax2 = fig1.add_subplot(5, 2, i+1)
    sns.kdeplot(X0_train.iloc[:, i+12],fill=True, color='k', facecolor='#c7ddf4', ax = ax2)
    ax2.set_xlabel(x_labels_cpx[i] + ' [wt. %] in cpx')
fig1.align_ylabels()
fig1.tight_layout()
```

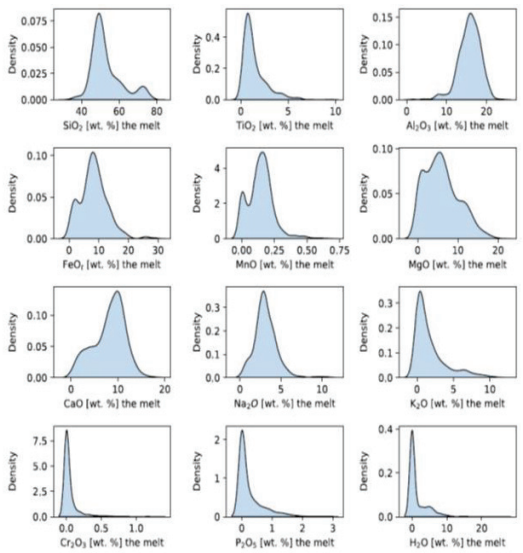

Fig. 7. Machine learning for predicting pyroxene formation temperatures

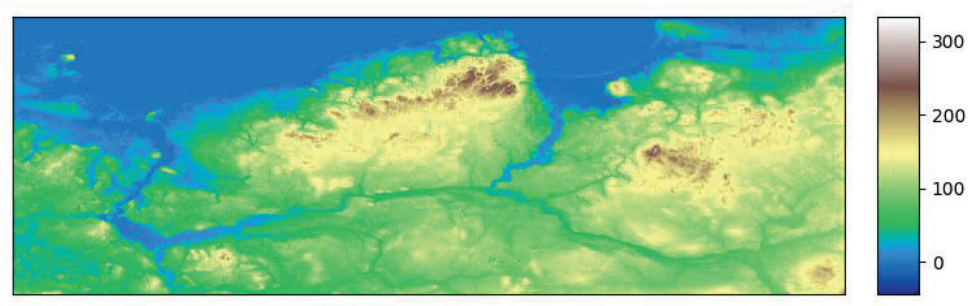

Fig. 8. Land cover classification using Landsat data and Python machine learning

CONCLUSION

4.1 SUMMARY

This research demonstrates applications of the Python programming language for data analysis, modeling, and visualization tasks commonly performed in earth sciences. The capabilities of Python ecosystems are showcased through sample workflows related to climate, geospatial, and machine learning analysis using real-world datasets.

Specifically, the analysis focuses on leveraging Python packages including Anaconda, Xarray, Numpy, scikit-image for implementing workflows relevant to earth science researchers. The Anaconda distribution provides a bundled suite of libraries tailored for scientific computing. Xarray extends Pandas for working with multidimensional labeled arrays. Numpy enables high-performance numerical computing with n-dimensional arrays. Scikit-image provides image processing algorithms. For climate data analysis, sample workflows ingest, process, and visualize precipitation datasets from the ERA5-Land global reanalysis. Xarray is used to load the NetCDF dataset, with Pandas utilized to structure the tabular data. Mathematical operations and aggregations analyze annual and long-term precipitation trends. Visualizations including anomaly maps and rainfall charts are generated with Matplotlib to uncover insights from the data. This demonstrates Python's capabilities for processing climate time series data.

For geospatial analysis, the research showcases leveraging scikit-image to programmatically process an elevation model from GloVis. Raster analysis techniques including hillshading and sun-illumination modeling are applied to the DEM. This enables creating shaded relief visualizations by specifying azimuth angles and sun positions. The image processing module streamlines generating enhanced DEMs. Scientific computation techniques in Python are exhibited through a numerical integration example. Approximating irregular volumes is solved by discretizing the shape into prisms and applying Simpson's rule. This demonstrates Python's mathematical libraries for enabling complex geometric computations.

A machine learning example predicts pyroxene formation temperatures based on chemical composition using sklearn and Pandas. After standard feature preprocessing, a random forest regressor model is trained on the dataset. Performance metrics show accurate predictions, with the model generalizing well to unseen data. Feature importances provide insights into prediction patterns. Satellite image classification is also demonstrated using Landsat data and random forest classifiers for land cover mapping. This enables automating the generation of thematic maps from raw spectral bands.

Overall, the analysis highlights the breadth of Python's capabilities for earth analytics encompassing data access, preparation, analysis, modeling, visualization and geospatial processing. Workflows can be consolidated into reusable scripts and automated pipelines. Python empowers researchers with a versatile toolkit tailored for programmatic earth data science. The examples provide templates for extending Python to new domains and datasets.

4.2 KEY BENEFITS

Some of the key advantages offered by Python:

- Productivity: Python provides high-level data structures, functions and abstraction that speed up development.
- Code Readability: Python code uses intuitive naming, indentation and coding style that improve maintainability.
- Open Source Ecosystem: Python has abundant libraries and packages for earth science applications accessible freely.
- Versatility: Python can be used for GIS, modeling, machine learning, cloud computing, IoT applications and more.

- Scalability: Python code can leverage parallel computing and hardware acceleration to handle large workloads.
- Reproducibility: Python workflows can be consolidated into reusable scripts, notebooks and applications.

4.3 Future Outlook

Looking ahead, we can expect Python's footprint in earth sciences to continue expanding. Upcoming trends like big data, open science, and artificial intelligence will further highlight Python's strengths.

Some growth areas include:

- Cloud-native analysis using Dask, GeoPandas on cloud object stores.
- Deep learning models for hazard forecasting, climate projection etc.
- Leveraging Python in real-time sensing platforms and instruments.
- Services providing on-demand computing and geospatial processing using Python.
- Domain-specific Python packages and conferences for earth science communities.
- Education and training programs focusing on Python for earth analytics.

4.4 Conclusion

In summary, Python delivers a scalable, open-source solution tailored for programmatic access and analysis of structured and unstructured earth data. It presents transformative potential for automating workflows, reducing duplication, enabling reproducibility across earth science disciplines. This article provided a sample of Python capabilities - the possibilities are endless.

For earth science students and researchers looking to learn their first or next programming language, Python is highly recommended as a future-proof skillset. The time invested in becoming proficient with Python libraries pays rich dividends in terms of workforce preparedness. Python fluency allows tapping the growing deluge of open earth data to advance scientific discovery for societal benefit.

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