Highlights

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- PyLUSAT is an open-source Python package dedicated to land-use suitability analysis
- An alternative solution for urban planners to conduct GIS-based suitability modeling
- Enabling rapid, massive simulation of future land-use scenarios in high-performance computing clusters
- PyLUSAT functions are computationally efficient, highly extensible, and cross-platform compatible
- It has been successfully implemented on HiPerGator, a supercomputer at the University of Florida
PyLUSAT: An open-source Python toolkit for GIS-based land use suitability analysis

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Abstract

Desktop GIS applications, such as \textit{ArcGIS} and \textit{QGIS}, provide tools essential for conducting suitability analysis, an activity that is central in formulating a land-use plan. But, when it comes to building complicated land-use suitability models, these applications have several limitations, including operating system-dependence, lack of dedicated modules, insufficient reproducibility, and difficult, if not impossible, deployment on a computing cluster. To address the challenges, this paper introduces PyLUSAT: Python for Land Use Suitability Analysis Tools. PyLUSAT is an open-source software package that provides a series of tools (functions) to conduct various tasks in a suitability modeling workflow. These tools were evaluated against comparable tools in \textit{ArcMap 10.4} with respect to both accuracy and computational efficiency. Results showed that PyLUSAT functions were two to ten times more efficient depending on the job’s complexity, while generating outputs with similar accuracy compared to the \textit{ArcMap} tools. PyLUSAT also features extensibility and cross-platform compatibility. It has been used to develop fourteen QGIS \textit{Processing Algorithms} and implemented on a high-performance computational cluster (HiPerGator at the University of Florida) to expedite the process of suitability analysis. All these properties make PyLUSAT a competitive alternative solution for urban planners/researchers to customize and automate suitability analysis as well as integrate the technique into a larger analytical framework.

Keywords: Land use planning, Suitability modeling, GIS, Geospatial analysis, Python, Open source
1. Introduction

Since first being introduced in late 1960s, Geographic Information System (GIS)-based suitability analysis continues playing a significant role in contemporary practices of land use planning (Collins, Steiner, and Rushman, 2001). It is particularly favored by land-use practitioners because the technique can effectively synthesize spatial analytics, expert knowledge, and community values, all of which, from a planning perspective, are critical factors to consider when making land-use decisions. In practice, suitability analysis is usually performed using GIS applications with a Graphical User Interface (GUI), including ArcGIS and QGIS (Abdullahi et al., 2015; Mesgaran et al., 2017). And since both software applications provide a Python package (namely ArcPy and PyQGIS) as an interface to their respective functions, suitability analysis can also be performed through scripting. Because it allows researchers to customize and automate the analysis, the second approach is preferable when dealing with complex processes.

But tools offered by GIS applications are either constrained to run only within their applications or they require the presence of the main application. Additionally, some GIS application, like ArcGIS, are proprietary and Operating System (OS)-dependent. These restrictions of GIS applications act as a barrier to the integration of suitability analysis into a more comprehensive framework that involves a series of analytical components completed by multiple software. Instead, a programming library is an alternative solution which nullifies such integration barrier. At the time of writing, there exist a wide variety of programming libraries that are developed to study urban-related issues, with examples being UrbanSim—simulating urban real estate markets, OSMnx—analyzing street networks, and UrbanAccess—measuring transit accessibility (Waddell, 2010; Boeing, 2017; Blanchard and Waddell, 2017).

However, despite being an influential technique in land use planning, there lacks a programming library that is dedicated to suitability analysis. To fill in this gap, we present a free and open-source software (FOSS) package—PyLUSAT: Python for Land-Use Suitability Analysis Tools. PyLUSAT provides a complete set of tools that is capable of carrying out geospatial analyses entailed by suitability analysis; serves as an alternative solution for planners and researchers to perform suitability analysis; and offers a cross-platform programming library that can run on a supercomputer (most of which are based on Linux OS) to take advantage of High-performance computing (HPC) (Strohmaier et al., 2020).

In this paper, Section 2 reviews the literature and explains the choice of adopting a vector-based GIS approach. Section 3 describes the three major categories of
PyLUSAT functions including geospatial, transformation, and aggregation functions, which support the main tasks in a suitability analysis. Section 4 presents validation and performance evaluation of PyLUSAT functions. Finally, Section 5 summarizes the paper and briefly discusses future research.

2. Literature Review

2.1. Vector-based GIS approach

In GIS literature, many studies have discussed which data format—vector (a view based on discrete objects) or raster (a view based on continuous fields)—leads to a better representation of our world. For example, Egenhofer and Frank (1987) proposed an object-oriented data model to address the deficiencies of storing, manipulating, and querying spatial data in conventional relational database management systems (RDBMS). However, Goodchild (1989) argued that the object view is a continuation of a tradition inherited from Cartography, and the field representation is more realistic and accurate. Bian (2007) went a step further to generalize all environmental phenomena into three categories and discussed each category’s applicability of adopting the object representation. Admittedly, vector and raster representations operate on two distinct sets of logic, but they both stem from and partially exhibit human perceptions of the world. Instead of viewing them as competing or conflicting, we probably should deem vector and raster as complementary representations of the real world like Couclelis (1992) suggested “people manipulate objects, but cultivate fields”. Today, we find the two representations and their corresponding analytical methods co-exist in harmony in GIS applications, in spite of the attempts to develop a “general theory” of geographic representation (Liu et al., 2008; Goodchild, Yuan, and Cova, 2007; Winter and Frank, 2000).

Vector-based GIS routines were implemented in PyLUSAT primarily because it fits well conceptually with the object-oriented nature of Python, as the same choice made by other land-use modeling programs (Barreira-González, Gómez-Delgado, and Águilera-Benavente, 2015; Bolte et al., 2007). Furthermore, such approach has two additional advantages over the raster representation. First, vector-based GIS tools bypass the modifiable areal unit problem (MAUP) since measurements or statistics are not derived from a raster grid whose cell size is arbitrarily determined (Jelinski and Wu, 1996), but directly from individual objects. Secondly, a vector-based land-use model is more politically relevant since objects, e.g., property parcels, reflect and honor the land ownership. Just as Couclelis (1992, p. 67) argued that “it is at this lowest level of real estate . . . , that we find
the cultural grounding of the notion of space as objects”. Thus, land-use decisions made on individual vector units are relatively more feasible and realistic compared with the raster representation.

2.2. Geospatial development with open-source Python tools

Both R and Python are widely used in geospatial analysis, but when it comes to development, Python is far more general-purpose and versatile, which make it the true Swiss Army Knife of the two programming languages. There is an abundant resource of open-source geospatial packages in Python (Carreira, 2016). For I/O-related tasks, Fiona (Gillies and Others, 2011), an API of the OpenGIS Simple Features Reference Implementation (OGR), is capable of handling a variety of forms of vector data from local Shapefiles to data on stored on a PostGIS/PostgreSQL database. Shapely (Gillies and Others, 2007), a Python API of the Geometry Engine Open Source (GEOS), provides methods related to set-theoretic analysis and manipulation of planar features. GeoPandas (Jordahl et al., 2019) is arguably the most powerful open-source geospatial package when it comes to vector GIS, in that it merges the functionalities of the two packages above, plus the data structures of pandas (McKinney, 2010), a fast, flexible, high-level building block for data analysis in Python. For raster data inputs, Rasterio (Gillies and Others, 2013) based on the Geospatial Data Abstraction Library (GDAL) can deal with I/O related tasks as well as converting from (or to) vector data.

3. PyLUSAT Functions for Suitability Analysis

Functions in PyLUSAT adhere to vector-based GIS routines, i.e., taking vector input and generating vector output after performing one or more geospatial operations. In most cases, a PyLUSAT function takes a collection of polygons representing land units as input, in which a single uniform land-use decision can be made. For example, these polygons can be property parcel data or an output of a series of GIS operations using multiple datasets, such as the Integrated Decision Units (IDUs) (Bolte et al., 2007; Wu et al., 2015).

The classic suitability analysis framework contains three steps: (1) evaluate land units based on identified criteria, (2) transform the measurements to a uniform suitability scale, and (3) combine the results to generate a single suitability score for each land unit (Steiner, McSherry, and Cohen, 2000; Marull et al., 2007). Correspondingly, functions of PyLUSAT fall into three categories—geospatial functions, transformation functions, and aggregation functions, which together
can fully implement the framework. The rest of this section explains in greater detail how the three categories of PyLUSAT’s functions operate.

3.1. Geospatial Functions

The suitability of a parcel of land for a given land use depends greatly on its spatial relationship with the amenities, institutions, service providers, and natural features in the area. Therefore, the geospatial functions are crucial to understanding land-use suitability. PyLUSAT provides a variety of functions to evaluate spatial relationships among vector objects, such as calculating distance and density, examining topological predicates (Strobl, 2008), and interpolation.

3.1.1. Nearest Neighbor Search

Distance, a direct measurement of proximity, is one of the most fundamental factors determining land-use suitability. For example, due to agglomeration effects, land parcels in the vicinity of a central business district (CBD) (Ottaviano and Thisse, 2004) or urban sub-centers (Yang et al., 2019) are highly suitable for commercial uses, whereas residential uses often favor parcels remote from nuisances, such as quarries or poultry farms. In these examples, land parcels/units can be conceived as a source set paired with a second set, we call targets, where distance from a source to the nearest target affects suitability. Thus, calculating distance amounts to a search for the Nearest Neighbor (NN). To generalize, given a set of \( m \) sources, i.e., \( S = \{s_1, s_2, \ldots, s_m\} \), and a set of \( n \) targets, i.e., \( T = \{t_1, t_2, \ldots, t_n\} \), the distance between \( s_i \) and \( t_j \), the corresponding NN of \( s_i \) in \( T \), determines \( s_i \)’s suitability, from a proximity standpoint. We use \( d_e(s_i) \) and \( d_m(s_i) \) for the Euclidean and Manhattan distances, respectively, as defined by the following equations.

\[
d_e(s_i) = \min_j ||s_i - t_j||^2_2, \text{ for } j = 1, 2, \ldots, n \tag{1}
\]

\[
d_m(s_i) = \min_j ||s_i - t_j||^1_1, \text{ for } j = 1, 2, \ldots, n \tag{2}
\]

where \( s_i = (s_{i1}, s_{i2})' \) and \( t_j = (t_{j1}, t_{j2})' \) are in \( \mathbb{R}^2 \); \( ||||^2_2 \) denotes the Euclidean (or \( l_2 \)) norm, i.e., \( ||s_i - t_j||^2_2 = [(s_{i1} - t_{j1})^2 + (s_{i2} - t_{j2})^2]^{1/2} \); and \( ||||^1_1 \) denotes the Absolute-value (or \( l_1 \)) norm, i.e., \( ||s_i - t_j||^1_1 = |s_{i1} - t_{j1}| + |s_{i2} - t_{j2}| \). Note that, here, we use a single representative point, usually a centroid, to represent a land unit. Figure 1 provides an illustration of the NN search based on the Euclidean distance.

Evidently, the computational complexity for this process will be \( O(mn) \), if a brute-force search was conducted (Xiao and Biros, 2016). However, it would be
The Nearest Neighbor, in terms of Euclidean distance, of each source in the target set.

overly expensive when the magnitude of $mn$ is large. The function `pylusat.distance.to_point` uses `scipy.spatial.ckdtr` which implements a *sliding midpoint* method to construct *KDtree* (K-dimensional tree) objects to search for the NN more efficiently (Virtanen et al., 2020). Like regular KDtree construction, the sliding midpoint method attempts to split the data at the median (midpoint) on each axis first, but the plane will then slide to the closest point if a trivial (all points on one side of the plane) split occurs (Maneewongvatana and Mount, 1999). Such a process results in a KDtree whose height need not to be $O(\log(n))$, the height of a regular KDtree, which in turn makes the construction of KDtree less computationally expensive. Maneewongvatana and Mount (1999) have shown that this implementation offers a better performance in NN search, especially when data are clustered along one axis of $\mathbb{R}^2$.

### 3.1.2. Affine Transformation

When the target set is comprised of line features, an efficient approach to compute distances is to transform the line features from individual vector shapes to a raster grid. The function `pylusat.distance.to_line` implements this ap-
proach by using the Affine transformation defined by the following equation.

\[
\begin{bmatrix}
  v_x \\
  v_y \\
  1
\end{bmatrix} =
\begin{bmatrix}
  c & 0 & l \\
  0 & -c & t \\
  0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
  r_x \\
  r_y \\
  1
\end{bmatrix}
\]  \tag{3}

where \(c\) is the cell size used to rasterize the 2-D plane shaped by the extent of the line dataset; \(v_x\) and \(v_y\) are the \((x,y)\) coordinates of the vertices of the line features; \(l\) and \(t\) are the left and top bound of the 2-D plane; and, finally, \(r_x\) and \(r_y\) represent the row and column number of the cell located on the transformed raster grid. The affine transformation matrix (ATM), i.e., the augmented matrix in the equation, performs a linear transformation (a scaling and a rotation) followed by a translation (shifting the origin), which preserves the relative spatial relationship among the line features (Wheaton et al., 2012).

After applying an Affine transformation, the problem of calculating distance to line features reverts to a search for NN since lines are pixelated into a definite amount of cells, wherever any part of any line exists. Note that the precision of the calculated distances will depend on \(c\), the cell size of the converted raster grid. Figure 2 shows an example of the transformation whose ATM’s entries are \(c = 100, l = 5000, \) and \(t = 4500\).

![Figure 2: An Affine Transformation that converts lines features (left) to a raster grid (right).](image)
3.1.3. Density and Zonal Statistics

Density is an important instrument in suitability analysis since it directly, from a 2-D perspective, measures the intensity of land-use related activities/phenomena on a landscape. For example, the density of single-family dwelling units in a given region reveals characteristics of the neighborhood, and the density of a road network reflects the level of accessibility it provides to vehicles. Because of its vector-based characteristic, PyLUSAT’s density module calculates density within a user-defined set of input zones (polygons). Using an analogy of source and targets in the distance definition, the density of targets in a given source zone \( i \) is defined as 
\[
\rho_i = \frac{\sum_{j=1}^{m} t_j v_j}{A_i},
\]
where \( t_j = 1 \), if target \( j \) is within the area of \( i \) \((A_i)\); otherwise \( t_j = 0 \), and \( v_j \)—the value corresponding to target \( j \)—equals to 1, if not specified.

To evaluate spatial containment of point targets, we used the function geopandas.sjoin, which supports three types of topological predicates: intersect, contain, and within. When targets are line features, PyLUSAT will first apply an Affine Transformation to convert them to a raster grid, and then use rasterstats.zonal_stats to calculate the total amount of cells within each source zone. Figure 3 illustrates the case of calculating line density.

3.1.4. Interpolation

Interpolation methods are used to estimate values of unknown data points using the known ones, of which the Inverse Distance Weighted (IDW) interpolation is widely applied in GIS-based suitability analysis (Tercan and Dereli, 2020; Varatharajan et al., 2018; Yao et al., 2013). Borrowed from mathematics, IDW, as a GIS technique, is one of the classic realizations of the so-called first law of geography: “everything is related to everything else, but near things are more related than distant things” (Tobler, 1970, p. 236). The most commonly adopted version of IDW is Shepard’s (1968) method defined below.

\[
f(P) = \begin{cases} 
\sum_{i=1}^{N} (d_i)^{-u} z_i & \text{if } d_i \neq 0 \text{ for all } i = 1, 2, ..., N. \\ 
\sum_{i=1}^{N} (d_i)^{-u} & \text{if } d_i = 0 \text{ for some } i = 1, 2, ..., N. 
\end{cases}
\]

(4)

, where \( P \) is the point of interest, \( z_i \) and \( d_i \) are, respectively, the value at the \( i \)-th known data point and its Euclidean distance to \( P \), and \( u \) is a predefined positive number also known as the power parameter. Note that, the negative sign before \( u \) makes the \( i \)-th point’s weight inversely proportional to its distance to \( P \) in the estimation, hence how the method got its name. Also, as distance increases, the
known values’ influences on the estimation of $P$ declines faster as $u$ gets bigger, which shifts the algorithm from a global model to a local model. The process of determining the best value of $u$ is relatively deterministic. PyLUSAT provides a function, `pylusat.interpolate.idw_cv`, which allows users to pick a proper value for $u$ through Cross Validation.

3.2. Transformation Function

The goal of transformation functions is to translate measurements based on various criteria into a standardized “suitability” scale, which is arbitrarily chosen and then consistently applied throughout the analysis, for example, a scale of 1 to 9 (the lowest to highest suitability) adopted by the Land Use Conflict Identification Strategy (LUCIS) (Carr and Zwick, 2007). In general, there are three mechanisms to define a transformation, which are by (a) unique categories, (b) range of classes, and (c) continuous functions. The first mechanism typically deals with nominal and ordinal data, in which individual values are associated
with different degrees of suitability. The second method handles interval or ratio data and is more flexible, in that values fall into a certain range represent the same degree of suitability. PyLUSAT’s `rescale.reclassify` function allows users to do both transformations by leveraging the pandas.DataFrame object’s highly efficient indexing/slicing capability.

Besides pre-defined ranges, ranges can be derived from the data as well. Jenks (1977) developed the natural breaks algorithm, originally as a choropleth mapping technique, which was widely employed in land-use suitability analysis (Abdullahi et al., 2015; Berry and BenDor, 2015; Owusu et al., 2017). Natural breaks seek to simultaneously minimize the differences within classes and maximize the differences between classes. The total variance in the data, also known as the squared deviation from array mean (SDAM), is defined as \( \sum_{i=1}^{n} (x_i - \bar{x})^2 \), on the other hand, the within-class difference is captured by the squared deviation from the class mean (SDCM), that is \( \sum_{j=1}^{k} \sum_{i=1}^{n_j} (x_i - \bar{x}_j)^2 \), where \( n_j \) is the number of elements in the \( j \)-th class, and \( k \) is a pre-defined number of classes. The algorithm iterates through all possible breaks and computes the Goodness of Variance Fit (GVF), i.e., \( \frac{SDAM-SDCM}{SDAM} \). The minimum GVF obtained corresponds to the so-called “optimal” range of classes.

As for transforming by continuous functions, PyLUSAT currently supports only a linear transformation, but we intend to release a complete list of functions in the next major update of the package. Although the linear transformation, also known as the min-max feature scaling, is relatively simple, it has been used as a feature engineering technique in many machine learning applications (Tang, Tan, and Chen, 2018). Besides the intuitiveness, another advantage that might make the method appealing in suitability analysis is that it preserves the distribution of the original variable after the transformation (Cao and Obradovic, 2015). Without loss of generality, the following equation defines a linear transformation of a variable \( X \) from its original scale \([x_{\text{min}}, x_{\text{max}}]\) to an arbitrary scale \([a, b]\).

\[
x'_i = \begin{cases} 
  a + \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}(b - a) & \text{for } i \in \{1, 2, \ldots, n\} \text{ (regular order)}. \\
  b - \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}(b - a) & \text{for } i \in \{1, 2, \ldots, n\} \text{ (inverse order)}. 
\end{cases}
\]  

(5)

, where \( n \) is the total number of observations. Note that, both cases in equation 5 are relevant to measuring land-use suitability. As with the two examples in Section 3.1.1, a relatively large value of the same measurement, i.e., distance, may be valued as either pros or cons, depending on the suitability criteria.
3.3. Aggregation Function

In GIS-based suitability analysis, transformed measurements of various criteria are combined to make a land-use decision, which commonly is done by assigning weights to individual criteria, based on expert knowledge, and then summing the results (Kalogirou, 2002). PyLUSAT provides a utility function `pylusat.util.weighted_sum` for such operation. However, professionals or stakeholders (agents) often find themselves in a situation where a consensus on the weighting cannot be reached. When this happens, a Multi-Criteria Decision Making (MCDM) technique is helpful. To address MCDM problems, PyLUSAT offers a function, `pylusat.utils.ahp`, to implement the Analytic Hierarchy Process (AHP) developed by Saaty (1990).

Based on the premise that people are good at comparing two (but no more than two) items, AHP converts a decision of multiple criteria into a series of pair-wise comparisons, with the result quantified using a scale from 1 to 9. If item A is equally important to item B, the result is 1. And, if item A is extremely important than item B, the result is 9. The integers in between correspond to different levels of pair-wise importance comparisons. Moreover, the reciprocals of these values are used if one swaps the comparates, i.e., if \( w_A / w_B = 5 \), then \( w_B / w_A = 1/5 \). According to this setup, AHP first creates a reciprocal matrix using results of the pair-wise comparisons. Then, it solves the eigenvalue equation, i.e., \( A\mathbf{v} = \lambda \mathbf{v} \), and retains the primary eigenvalue (the largest one among all eigenvalues) and the corresponding primary eigenvector. Finally, it normalize the primary eigenvector (dividing individual elements of the vector by their sum), to obtain the priority vector. Each element of the priority vector represents the weight of an initial criterion involved in the analysis, which reflects its relative importance in the final decision.

AHP also involves a mechanism, Consistency Ratio (CR), to validate whether the decisions of the pair-wise comparisons are consistent, e.g., given \( w_A / w_B = 7 \) and \( w_B / w_C = 3 \), then if \( w_A / w_C = 1/5 \), we call it an “inconsistency” in the comparisons. In addition to the `pylusat.utils.ahp` function, PyLUSAT also provides a `pylusat.utils.random_ahp` function to generate random AHP weights that follows the rule of thumb, that is CR is less than 0.1.

4. Validation and Evaluation

Figure 4 shows two choropleth maps side-by-side, where the left one presents the result of measuring point distances between schools and centroids of census block groups (CBG) of Alachua County, Florida; and the right one shows the
same phenomenon with the same color scheme but measured by PyLUSAT. The datasets used to create the two maps, the left by a layout of ArcMap and the right by the plotting function of GeoPandas and Contextily (for basemap tiles), are included in the GitHub repository mentioned in the first section. As the figure shows, from a cartographic perspective, the two results are identical. However, to validate tools in PyLUSAT, especially the geospatial functions, more rigorously, we compared outputs of five geoprocessing tools in ArcMap 10.4 with the outputs of corresponding functions in PyLUSAT by conducting a series of (two-tailed) paired-sample $t$-tests. The null hypotheses of these tests are identical, which is there exists no statistically significant difference between outputs from PyLUSAT functions and their ArcGIS counterparts. Table 1 lists (by function) the degree of freedoms (df), observed $t$ statistics, and $p$-values of these $t$ tests. In these $t$

| Test function          | df  | $t$ statistic | $p$-value |
|------------------------|-----|---------------|-----------|
| Distance to point      | 154 | 1.0528        | 0.2941    |
| Distance to line       | 154 | 0.3613        | 0.7184    |
| IDW                    | 154 | 0.5889        | 0.5568    |
| Density of point       | 154 | -0.6863       | 0.4936    |
| Density of line        | 154 | 1.1656        | 0.2447    |

Table 1: Paired-sample $t$-tests between results from PyLUSAT and ArcGIS.
tests, the observations are different quantities measured against the 155 CBGs in Alachua County, hence 154 df. We used school and road network datasets in the county for point and line features respectively which, again, are included in the GitHub repository. For IDW, we used the Digital Elevation Model (DEM) as the value raster grid. As indicated by the $p$-values, none of the tests can reject the null hypothesis, which suggests that we can trust the results of PyLUSAT’s geospatial functions with confidence.

PyLUSAT is developed with computing speed in mind as well. In contrast to conducting suitability analysis using GIS applications, computational efficiency is mainly gained from two sources: (a) the implementation of *NumPy*’s vectorized operation in PyLUSAT and (b) the I/O wait time saved from reading/writing intermediate files (Harris et al., 2020). The latter is non-negligible in that GIS applications need to store intermediate files on disk, whereas PyLUSAT keeps the study units (e.g., land parcels) in memory throughout the entire process of suitability analysis. Figure 5 shows three time cost (wall time measured in seconds) comparisons between PyLUSAT functions and their counterparts in *ArcMap 10.4*. Note that, `pylusat.density.of_line()` calculates line density in each input polygon or in a user-defined radius around each polygon’s centroid. Since the function is different from *ArcMap*’s *Line Density* tool, which only produces a raster grid with density values, a ModelBuilder model consisting of *Line Density* and *Zonal Statistics* was used in the third comparison. As shown in the figure, PyLUSAT functions take less time to run in all three cases, and such effect become more significant as the total number of measurements increases.

The improved computational efficiency by individual PyLUSAT functions could significantly reduce the total time cost of conducting a suitability analysis. Moreover, this effect can be further amplified by HPC. Since PyLUSAT is cross-platform, it can be installed on a computing cluster (usually running on Linux-based OS) with minimal effort. Thus, it enables urban planners and researchers to rapidly simulate future land-use scenarios to evaluate both the intended and unintended consequences of specific land-use policies under the framework of suitability analysis. This is a main goal of the development of PyLUSAT. Chen (2019) conducted a feasibility study, in which PyLUSAT is used to port the LUCIS model to *HiPer-Gator*, a supercomputer at the University of Florida (Carr and Zwick, 2007). In this study, ninety-six cores were used to simulate 120 alternative land-use scenarios in Orange County, Florida. The entire process took only slightly over five minutes.
Figure 5: Running times for PyLUSAT functions compared with their ArcGIS counterparts.

5. Conclusion

Open-source software dedicated to GIS-based land use suitability analysis is rarely found in relevant literature. In this paper, we present a Python package—PyLUSAT—representing a promising candidate to help fill in this absence. As an alternative solution to existing GIS applications, PyLUSAT facilitates the customization and automation of suitability analysis while maintaining the process highly scalable and reproducible. The performance of PyLUSAT’s functions were evaluated from both accuracy and efficiency perspectives. Five geospatial
functions in PyLUSAT were selected and conducted paired-sample $t$ tests between the outputs from these five functions and outputs from their counterparts in ArcMap 10.4. Results of these tests showed that there are no statistically significant difference between the two sets of outputs. Additionally, we benchmarked the time costs (wall time) of three PyLUSAT’s geospatial functions and their corresponding tools in ArcMap. Results showed that PyLUSAT functions are noticeably faster.

PyLUSAT has been made available on the Python Package Index (PyPI) and also on GitHub at https://github.com/chjch/pylusat. It offers various tools (functions), allowing the package to handle tasks entailed by GIS-based land-use suitability analysis. PyLUSAT can be used not only on a personal computer running on either Windows, Linux, or MacOS, but also on a supercomputer to take advantage of HPC. In addition, PyLUSAT is highly extensible. For example, it is currently being used to develop fourteen QGIS Processing Algorithms to support sustainable land management (SLM) in Ghana (GALUP team, 2021). Finally, methods and tools introduced in Section 3 of this paper can be used by developers in the FOSS community who are interested in developing geospatial packages and applications.

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