Applications of Remote Sensing for Land Use Planning Scenarios With Suitability Analysis

Julie A. Peeling, *Graduate Student Member, IEEE*, Changjie Chen, Jasmeet Judge, *Senior Member, IEEE*, Aditya Singh, Silas Achidago, Alexander Eide, Katelyn Tarrio, and Pontus Olofsson

***Abstract*—In regions undergoing rapid urbanization, such as West Africa, land use planning (LUP) is vital to accommodate a growing population and manage natural resources. Suitability analysis modeling is a widely-used tool in LUP to determine the extent to which a land area is suitable for a designated purpose, but there is a gap in the integration of remote sensing time series data into land use decisions. The goal of this study was to incorporate remote sensing time series information with suitability analyses to inform LUP decisions in urban areas. In the study area of Kumasi, Ghana, land cover trends, and land surface temperature from 2000 to 2019 were used to understand climate change trends. Suitability analyses determined the fitness of land areas for predetermined uses. These background processes informed a genetic algorithm to project plausible futures for three land use scenarios. One scenario represented current LUP practices for addressing population growth, another scenario prioritized minimizing climate change impacts while also accommodating population growth, and the final scenario focused on both of these climate and population goals in addition to high density urban development. Each of these scenarios was successful in achieving population accommodation and respective climate change mitigation goals. The results for these scenarios provide insight into plausible land use distributions in 2050 based on different planning approaches. The genetic algorithm was able to effectively develop results for each scenario through the integration of remotely sensed trends and suitability models, providing a novel approach to land use decision-making.**

***Index Terms*—Genetic algorithm (GA), land surface temperature (LST), land use planning (LUP), remote sensing (RS) time series, suitability analysis.**

I. Introduction

URBANIZATION that has been occurring across the globe to accommodate growing populations, in addition to a changing climate, has increased the importance of effective land use planning (LUP) toward sustainability. Current LUP practices in developing areas often involve inefficient urban land allocation, with low-density developments and urban sprawl compromising agricultural and forested areas [1], [2]. A LUP approach that has proven successful in terms of climate adaptability is exploratory scenario planning, which assesses trends and causes of change to prepare for future conditions [3]. This type of scenario planning requires an understanding of environmental and socioeconomic trends to examine the driving forces of a rapidly developing area [3]. Environmental patterns and demographic data are thus heavily-researched inputs into LUP, but in developing countries, there is often a lack of information, such as ground-based GIS data [4], [5]. While remote sensing (RS) provides high-resolution datasets with global coverage, there remains an insufficient exploration of efficient methodologies to leverage this information for land use analyses. [5].

RS applications in the field of LUP that have been previously explored include the detection of land cover (LC) changes through static LC maps and the tracking of environmental patterns through remotely-sensed time series data [6], [7], [8], [9], [10]. Remotely-sensed LC maps allow for the assessment of existing land use conditions and investigation into methods to improve consumption of land and resources [1], [6], [7]. Time series information, such as vegetation dynamics, water indices, and land surface properties, can provide insights into correlational and causal relationships between land transformation and environmental responses [10], [11], [12], [13], [14]. For example, studies have found that RS time series data indicators, such as land surface temperature (LST) correlated negatively to vegetation and water and positively to air pollution and urbanization [13], [15], [16]. LST has also been found to be highly correlated with urban heat islands (UHIs), which can significantly impact public health and environmental systems [13], [15], [17], [18]. The sensitivity of LST to LC and its close association with climate change makes it an important parameter to consider when making LUP decisions, especially in metropolitan areas [13], [16], [17]. With years of RS data, measures, such as LST are highly accessible for temporal analysis involving land use change and climate implications, providing essential knowledge for LUP [10], [12], [13], [15], [16].

An essential tool for LUP is suitability analysis, which determines the extent to which a land unit is fit for a designated purpose through examining relevant natural and socioeconomic parameters, such as land condition, population density, road

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Julie A. Peeling, Jasmeet Judge, and Aditya Singh are with the Center for Remote Sensing, Department of Agricultural and Biological Engineering, University of Florida, Gainesville, FL 32611 USA (e-mail: jap479@cornell.edu).

Changjie Chen is with the Florida Institute for Built Environment Resilience, University of Florida, Gainesville, FL 32611 USA.

Silas Achidago is with the Department of Urban and Regional Planning, University of Florida, Gainesville, FL 32611 USA.

Alexander Eide is with Kittelson & Associates, Inc., Miami, FL 33130 USA.

Katelyn Tarrio is with the Department of Earth, Environment, Boston University, Boston, MA 02215 USA.

Pontus Olofsson is with the NASA Marshall Space Flight Center, Huntsville, AL 35808 USA.

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systems, and vegetation [19], [20], [21], [22], [23]. Suitability analysis can be conducted in conjunction with techniques, such as multiple criteria decision analysis (MCDA), which aids decision making using criteria and weights to evaluate the trade-offs and possibilities of complex problems [24]. The analytic hierarchy process is a widely used MCDA technique that has been successfully employed to examine land use suitability and support strategic decision making [22], [24]. Suitability analyses for various land use categories provide insights about interactions among input variables to guide the LUP decision making based on specific goals [20], [21], [22], [23]. Current suitability analysis methods employ static LC maps of recent conditions to inform on land distribution patters [25]. However, such a static view neglects factors that are inherently latent but can potentially influence the dynamics of the land use system and the trajectory of change. Through directly incorporating RS time series data alongside suitability analyses into LUP, future scenarios can be better projected.

In West Africa, rapid urban expansion in recent decades has been the result of population growth and migration to cities. This urbanization, in conjunction with climate change, has led to environmental degradation and deforestation [6], [26]. For example, in Ghana, high population growth, especially in central urban areas, such as the city of Kumasi in the Ashanti Region, has resulted in land use allocation issues [27], [28]. Exploratory scenario planning applied to rapidly expanding urban areas, such as Kumasi, can help promote sustainable LUP and address social and environmental needs.

The optimization of land use scenarios is a complex process due to multiple land use allocations across different spatial units. This is a challenge because not only does each land use have its own requirements from a parcel of land, but the land use types are also competing for use of the same space. In response to the complexity of land use allocation, many methods for scenario planning have been developed. In earlier studies, hierarchical optimization and linear programming were applied, but these approaches are limited in their ability to account for spatial objectives [29], [30]. In more recent studies, cellular automata and heuristic algorithms have become more common. Cellular automata are commonly used due to their simplicity and flexibility, but this approach focuses on changes in singular land units across time instead of considering the landscape interactions as a whole [31]. Heuristic algorithms are effective tools for identifying optimal solutions, and methods, such as simulated annealing, particle swarm optimization, ant colony optimization, and genetic algorithms (GAs), have been applied for land use optimization [29], [30], [32]. GAs were introduced in the mid-1970s [33], applying the principles of natural selection to evolve toward an optimized scenario. An advantage of GAs over other heuristic algorithms for land use optimization is their flexibility to accommodate multiple objectives into the program [34]. These algorithms have also been widely applied to land use optimization because the evolutionary process provides efficient convergence, and the generation of a nondominated set can allow for analysis of additional cases [29], [30], [32]. GAs represent a robust approach for large and diverse landscapes [32]. However, the drawback of this method is that GAs are computationally intensive and may be inefficient [32], [34].

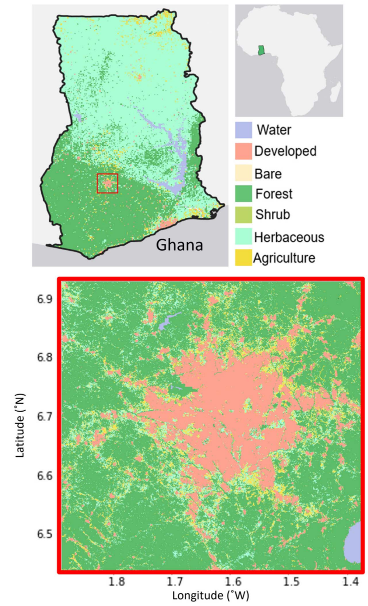

Fig. 1. GLanCE classification of Ghana and the study area, the greater Kumasi area (bottom).

The aim of this study is to understand the impact of incorporating remotely-sensed land use and environmental trends and current suitability conditions on future land use allocations. The main objectives of this article are as follows.

1) Conduct land use suitability analyses on competing land use types in the study region encompassing the greater Kumasi area.
2) Use RS time series trends to quantify the relationship between land use change and LST increases.
3) Integrate suitability analyses and RS information from the above objectives using a GA to analyze exploratory planning scenarios for Kumasi, Ghana.

Such exploratory planning is conducted for the prediction of future land uses in the next 25 years based on U.N. and IPCC projections of climate and population [35], [36], [37].

II. Methods

A. Study Area

The study area is the urban center of Kumasi in South Central Ghana (see Fig. 1). The current population of Kumasi is about 3.6 million, but it has increased by about 2 million people in the last 20 years, indicating the rapid urban expansion that it is experiencing [36], [38]. The study was conducted using the military grid reference system, which is a NATO geocoordinate standard, with a pixel size of 250 m. These pixels served as decision units for each land use. A box around Kumasi, containing 2426 km^2, served as the study area to incorporate the lands most likely to experience land use changes due to urban expansion by 2050 [39].

B. Data Acquisition

The remotely-sensed data was acquired through Google Earth Engine. The LST data used in this study was calculated from

TABLE I
OPEN-ACCESS DATA FOR THE RS TIME SERIES DATA AND SUITABILITY MODELS

Variable	Source	Spatial Resolution	Year	Application
LST	Landsat 7 and 8	30 m	2000–2019	RS time series
LC	Landsat 5, 7, and 8 (Boston University)	30 m	2000–2019	RS time series
Soil pH	ISRIC	250 m	2015	Agriculture Suitability
Root Zone Depth	ISRIC	250 m	2015	Agriculture Suitability
Soil Drainage	ISRIC	250 m	2015	Agriculture Suitability
Topography	SRTM	90 m	2018	Agriculture Suitability
LC	Boston University	30 m	2019	Agriculture Suitability
Roads	OpenStreetMap	-	2020	Agriculture and Urban Suitability
Population Density	Worldpop	200 m	2020	Urban Suitability
Distance to Settlement	Worldpop	200 m	2020	Urban Suitability
Protected Forest	LUSPA	-	2000	Forest Suitability
Forest Coverage	Biomass Geo-Wiki	1 km	2015	Forest Suitability
Inland River	World Agroforestry Center	-	2020	Forest Suitability

Landsat 7 and 8 bands at a 30 m spatial resolution using an algorithm developed by Avdan and Jovanovska [40]. Landsat-based LST data was used due to its fine spatial resolution and temporal coverage across the study period [15]. Median LST values for the study area were extracted annually over the study period. The land classification data was extracted from maps through continuous change detection and classification. These maps were based in Landsat and generated using similar methods as described by Friedl et al. [41] to develop the Global Land Cover Estimation (GLanCE) LC dataset.

Various datasets were used for the suitability analyses, as given in Table I. These included soil condition, conservation, and development information and were acquired from environmental, social, and infrastructural sources.

C. Land Use Suitability Analysis

The suitability of a land unit can be assessed through determining its capability to fulfill a predetermined purpose. The process of a suitability analysis involves data inputs relevant to the given purpose, such as physical land characteristics, demographics, and economic information. These inputs are then contextualized to meaningful criteria (e.g., soil quality, urban centrality, or market availability) to inform suitability values [22], [42], [43]. Each criterion is transformed from its original scale to a common suitability scale. These criteria can be weighted on importance to the goal of the analysis.

Given the current land use dynamics in the greater Kumasi area, suitability analyses were conducted for three competing land use types in the study area: agriculture, forest, and urban. Forested areas were considered to be conservation lands within the study area. These land use types were selected for analysis because they represent conflicting aims of LUP for conservation, urbanization, and food production, which are all strongly linked to population growth [42], [44], [45]. Land use priorities compete for space, especially in peri-urban areas that need to accommodate growing populations while maintaining agricultural land and mitigating deforestation [42], [44].

The suitability analyses of the three competing LC types were conducted at a 250 m resolution using PyLUSATQ tools in QGIS that were specifically developed for LUP purposes [23]. An analytic hierarchy process approach was employed through these tools to analyze the complex and often conflicting criteria across

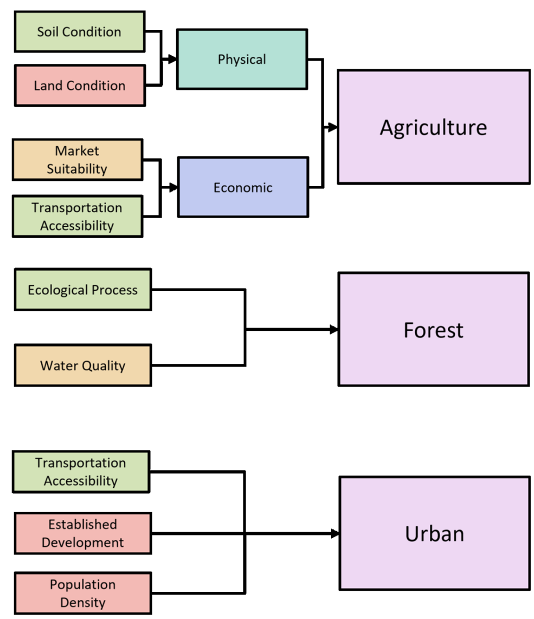

Fig. 2. Suitability models for the three competing land uses in the Kumasi area.

the land use types. Variables relevant to each land use as given in Table I were used to determine the respective suitability levels for each pixel within the study area. The suitability analysis models for each land use are given in Fig. 2. For agriculture, the suitability of a plot of land is dependent on its physical and economic characteristics [42]. For example, the soil layer is an important physical component when considering agricultural suitability because it determines crop growth, impacts erosion, and affects irrigation efficiency [22], [46]. Both soil condition and land condition provide insight into the physical suitability of the land while market suitability and transportation accessibility inform on the success of an agricultural business based on its location [42]. For forest land use, important aspects to consider include water quality and ecological characteristics, such as forest coverage and conservation, to determine potential longevity and durability of a forest. Urban suitability is dependent on aspects, such as transportation accessibility, pre-established development regions, and current population density, to follow the typical trend of urban expansion outward from a city center [39].

The resulting suitability values for each land use ranged from 1 to 9, where 1 is an indicator of low suitability levels and 9 represents high suitability [19], [42]. These suitability values were binned into three equally sized intervals and reassigned to a value of 1, 2, or 3 representing low, medium, and high preference, respectively [19], [42].

The suitability of the herbaceous land use type was also considered across the study area as a function of the distance between each herbaceous pixel and the nearest urban pixel. The suitability for each herbaceous pixel was quantified using a Beta probability distribution, where herbaceous pixels closer to urban areas had a lower suitability and pixels farther from urban areas had a higher suitability so as to encourage peri-urban herbaceous areas to become urban first. This suitability measure was only applied for the land use scenario with high density urban pixels, as high density urban expansion is more appropriate in close proximity to current urban areas.

Land use conflict occurs where two or more land use types have equal preference for a given land unit [19]. Naturally, land units that result in less land use conflict should be preferable for allocating the projected population growth by 2050, which is a primary objective in this study. To allocate additional population essentially means to designate more land units as urban (i.e., human settlements), which becomes the main impetus for land use changes in the region. For this study, conflict between urban and the other land use types occurred within urban areas when the urban preference of those areas was less than or equal to the preference of another land use. For an urban pixel, this conflict was quantified by the ratio of each land use preference to the urban preference of the pixel. If this ratio for a specific land use had a value less than 1, the urban conflict with that land use was set to 0 because this indicates that the the urban preference was greater than that of the given land use and thus there was no conflict. For each urban pixel within the study area, the total urban conflict was calculated through summing the individual conflicts with each other land use type. These pixel-wise total conflict values were then summed across all urban pixels within the study area to determine the overall urban conflict.

D. RS Time Series Analysis

The time series RS data consisted of annual LST and land classification information over the study period within the study area. The median annual LST images, in which each pixel contained a median LST value, were further processed to extract the annual mean LST values across each land class within the entire study area. This resulted in one mean LST value per land use type for each year of the study period to be input into an ordinary least squares (OLS) regression. To find the correlation between LST change and land use change, the OLS regression was conducted on the relationship between the annual number of pixels of each land use in the study area and the respective average annual LST value for each land use type to obtain the estimated change in LST per pixel of each land use type. The land classes included in this analysis were agriculture, forest, urban, and herbaceous, because these were the LC classes that underwent changes over the study period. The other LC present in the study area, water, was assumed to be constant over the next 25 years and thus was assigned no relationship with LST. The resulting relationships from the OLS regression indicate the magnitude of change occurring in LST across the study area over time with variations in land distributions.

E. Scenario Generation

In this study, three scenarios were developed to assess plausible future land use allocations for Kumasi in the next 25 years. These scenarios explored LUP pathways based on varying urban densities as well as differing sets of constraints concerning population accommodation and limitations on LST increases. The first scenario developed, designated as the "current trajectory scenario" (CTS), is based in current LUP practices and is representative of sprawling urban expansion that prioritizes convenience and does not consider climatic impacts of land use change [2]. The CTS is under one constraint of accommodating population growth and utilizes the current average density in the Kumasi area of 514. The second scenario, named the "constraint accommodation scenario" (CAS), focuses on both allocating the growing population while also limiting LST increases. The CAS also incorporates urban density of 514 people per urban pixel. The third scenario, the "high-density scenario" (HDS), accommodates the same population and LST constraints as the CAS, but it applies a high urban density of 1120 people per urban pixel for population allocation purposes. The high density measure was calculated with the average number of people per urban pixel in the center of Kumasi, where the urban density is highest.

The guiding population and LST constraints for these scenarios were based on projections for 2050, with the goal to accommodate population growth of 1 million people while mitigating LST increase to below 2°C [35], [47]. Kumasi is a rapidly-growing area in Ghana, so targeting population and climate concerns is an important consideration for LUP. Population growth is one of the main drivers of land use change to human settlements, as increasing amounts of space and resources are required to sustain a larger population [44]. LST is an important indicator of land use change, impacting socioeconomic factors and environmental conditions, especially through UHIs [12], [15], [17]. The LST limit was set to 2°C based on U.N. and IPCC targets, as well as studies predict that global warming above 2°C on average would result in temperatures outside of the range experienced by any human civilization [35], [37], [48]. Warming at this level would most likely result in severe and frequent climate events, such as droughts, heatwaves, and heavy rainfall [48].

F. Integrating RS With Suitability Analysis

Results for the CTS, CAS, and HDS were developed through a GA, integrating RS with suitability analysis into LUP. This process is given in Fig. 3. GAs are a type of evolutionary algorithm that are applied to constrained optimization problems and are based on the principles of natural selection. This method has been used previously with RS data to optimize water management under a set of constraints because of its flexibility and

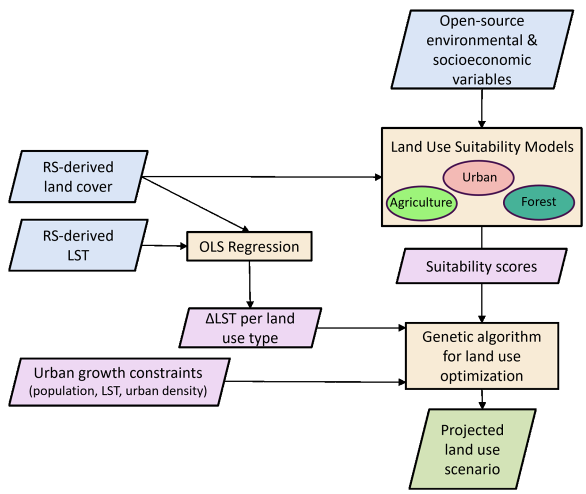

Fig. 3. Overall process for integrating suitability analysis and RS time series information into the GA under constrained urban growth scenarios. In the flow diagram, RS, OLS, and LST represent RS, OLS, and LST, respectively.

ability to accommodate customized constraints and goals [49], [50]. The GA method has been studied to guide LUP efforts and optimize land allocation with multiple objectives [29], [30], [51].

The GA is initialized with a population that then mutates and crosses over until an optimal individual is achieved. The GA was initiated with a population of 20 individual land use distributions. Diversity in this initial population was implemented to increase the effectiveness of crossover and mutation for convergence [29]. Out of the 20 initial individuals, eight were a copy of the current land use in Kumasi, four prioritized agricultural land use, four prioritized forest land use, and four prioritized urban land use. We utilized a Jenks distribution, a 1-D classification system, in conjunction with the suitability values of each land use type to create the prioritized distributions that added the initial diversity [52].

After initialization, the next phases in the algorithm are crossover and mutation. In this application, crossover involves the swapping of land use types between two individuals [29], [30]. Mutation occurs through the conversion of one land use type to another [29], [30]. These are both variable parameters based on random selection. The probability of crossover occurring for each individual was set to 60% and the probability of mutation set to 20%. The probability of each pixel crossing over was set to 50%, and the probability of each pixel mutating was set to 5%. These parameters served to increase the speed at which the algorithm converged. In traditional GA processing, the crossover and mutation occurs on genes of a chromosome, which is 1-D. For this application, because the land use individuals are 2-D, the typical methods for these processes result in decreased organization and contiguity. To address this issue, we followed a crossover and mutation methodology described by Wang et al. [30]. Each of these operations was conducted on 3×3 grids within the individuals in order to increase contiguity and compactness among the land use types [30], [34]. Crossover occurred through swapping pixels from two individuals where there would be pixels of the same land use type as the swapped pixel in the 3×3 grid surrounding it [30]. Mutation operated as a 3×3 grid of one land use type identified as insufficient replacing an area containing a land use type determined to be in excess [30]. For this study, agriculture, urban, and forest land uses were specified as insufficient and herbaceous land was identified to be in excess. The methods for crossover and mutation were implemented to result in a higher compactness of land use types within the next-generation individuals [30]. Compactness is an important consideration in LUP because it ensures that land uses are more contiguous and thus more functional. For example, it allocates urban development near to current urban areas and forested lands close to current forests. For both mutation and crossover, a mask was implemented to exclude water from being converted from or to, in accordance with the assumption that water bodies would remain constant between the original land use and 2050. In addition, a condition was added to the algorithm for the original urban areas to remain urban across each generation. The development of a land area tends to be an irreversible process that prevents urban lands from being converted to other land uses, so while other land use types could be converted into urban, the reverse was prevented [53].

The GA was structured using constraints and objectives to guide the algorithm toward an optimal land use result. The optimization occurred through selecting the most fit individuals in the current generation to pass on their characteristics to the next generation. The fitness of an individual was based on adherence to constraints, additive objectives, and spatial objectives, and this was quantified through an evaluation score. The goal of the GA was to minimize this score, indicating a high fitness and thus optimal land use individual [29], [30]. Through the LST constraint evaluation, RS was integrated into the GA by utilizing the slope relationships from the OLS regression on the RS time series and land use data. These land use-specific slopes represent the change in LST per pixel of each land use type. For each land use individual within a generation of the GA, the total change in LST across the study area was calculated through multiplying the respective land use slopes by the change in pixels of each land use type from the original land use individual. This total change in LST for the land use individual was then evaluated with respect to the LST constraint. This is shown in the following, where ΔT represents the change in LST from the original land use individual to the individual being evaluated and T_{goal} is the LST constraint set to an increase of 2°C

$$\text{eval}_{\text{LST}} = \left(\frac{\Delta T - T_{\text{goal}}}{|\Delta T|}\right)^2. \quad (1)$$

The population growth constraint was determined by calculating the number of urban pixels needed to accommodate the growing population. This number was found under an assumption of a constant urban density across the study area, which differed between 514 or 1120 people per urban pixel, depending on the scenario. The calculation to evaluate how well the population growth constraint was met is given as follows:

$$\text{eval}_{\text{pop}} = \left(\frac{u_{\text{needed}} - u_{\text{current}}}{u_{\text{needed}}}\right)^2 \quad (2)$$

where u_{needed} is the number of urban pixels required for accommodating the population growth and u_{current} is the number of urban pixels that the individual being evaluated contains. The additive objectives in the algorithm included urban conflict and land use suitability, which utilized the results of the suitability analysis [34]. Across the land use individual, the urban conflict values within each urban pixel were summed. The algorithm was penalized at high magnitudes of conflict between urban and other land uses. Land use suitability was evaluated using the values from the suitability analyses. For CTS, the suitability of only urban pixels was summed and included in the evaluation score, as this scenario prioritized the best placement of urban areas. In CAS, the suitability of the assigned land use type of each agricultural, forest, and urban pixel was extracted and summed to a total suitability. The suitability objective calculated for HDS summed the suitability value of each agricultural, forest, urban, and herbaceous pixel, as the high density parameter requires the conversion of fewer herbaceous pixels and prioritizes urbanization closer to the city center. The spatial objective was compactness, which was determined by selecting each pixel and calculating the proportion of surrounding pixels with the same land use as the selection. These values were summed across the entire land use grid. The evaluation score component from these additive and spatial objectives was calculated by linearly scaling the computed urban conflict, suitability, or compactness in relation to the minimum and maximum values for the study area, as shown in (3), (4), and (5). The aim was to minimize the overall conflict and maximize suitability and compactness

$$\text{Conf} = \frac{\text{conf}_{\text{current}} - \text{conf}_{\text{min}}}{\text{conf}_{\text{max}} - \text{conf}_{\text{min}}} \tag{3}$$

$$\text{Suit} = \frac{\text{suit}_{\text{current}} - \text{suit}_{\text{max}}}{\text{suit}_{\text{min}} - \text{suit}_{\text{max}}} \tag{4}$$

$$\text{Spa} = \frac{\text{spa}_{\text{current}} - \text{spa}_{\text{max}}}{\text{spa}_{\text{min}} - \text{spa}_{\text{max}}}. \tag{5}$$

In (3), $\text{conf}_{\text{current}}$ represents the total urban conflict within an individual land use scenario in the current generation of the GA. This measure was calculated by summing the urban conflict values across the urban pixels in the individual. Similarly, $\text{suit}_{\text{current}}$ represents the overall suitability of an individual in the current generation, calculated by summing the land use-specific suitability values of each pixel. The $\text{spa}_{\text{current}}$ variable measures overall spatial compactness within an individual in the current generation. This measure was quantified through first calculating, for each pixel, the proportion of surrounding pixels with the same land use type, and then these pixel-wise values were summed across the individual. The conf_{min} variable was set to 0, indicating a situation where, for the urban pixels in an individual, the land use-specific preferences are all less than the urban preference values and thus there is no urban conflict. conf_{max} represents the maximum potential urban conflict and was calculated by summing the urban conflict if all pixels in the study area were allocated to be urban. The suit_{min} variable was defined as the sum of suitability values across the original land use individual, as the aim was for overall land use suitability to increase throughout the GA. suit_{max} represents the maximum suitability that could be achieved across the study area and was calculated as the sum of suitability values in the individual if each pixel had a suitability of 9 (highest). spa_{min} was set to the compactness value of the original individual, with the aim to increase overall compactness over the course of the GA, and spa_{max} was set to the number of pixels in the land use grid, representing complete compactness with one uniform land use type.

The additive and spatial objectives and the constraints make up the total evaluation score, and the GA was programmed to minimize this measure through iteration. This essentially optimizes the process of minimizing urban conflict and temperature change (where applicable) while maximizing compactness, suitability, and urbanization needed to accommodate a growing population. The individual with the lowest evaluation score across all generations is selected as the result for the algorithm. The calculation of the evaluation score is given for CTS in (6), and for CAS and HDS in (7)

$$\text{Min}_F = \text{Suit}^p Sapa^p + \text{Conf}^p \text{Spa}^p + \text{eval}_{\text{pop}} \tag{6}$$

$$\text{Min}_F = \text{Suit}^p \text{Spa}^p + \text{Conf}^p \text{Spa}^p + \text{eval}_{\text{temp}} + \text{eval}_{\text{pop}} \tag{7}$$

where p is a penalty coefficient that serves to magnify the effects of a large, and thus unfit, evaluation score component. This value was set to 4, as supported by past literature [29]. The overall process followed by the GA is outlined in Fig. 4.

The GA was implemented using DEAP, a Python library developed for evolutionary algorithm optimization [54]. This library was developed to be compatible with parallelization through the SCOOP software module in Python. The parallelization capabilities of SCOOP, in conjunction with high-performance computing (HPC), were utilized to improve the efficiency of the algorithm.

III. Results and Discussion

A. Land Use Suitability Analysis

The results of the suitability analyses for agriculture, forest, and urban are given in Fig. 5. These results display the study area, with each pixel assigned a value based on the set of criteria defined for the specified land use. The most suitable areas for agriculture can be seen just outside of the urban extent, as this provides access to markets and transportation while still having access to land with high soil productivity. This phenomenon of agriculture on the urban periphery has been observed since the early 19th century, as theorized by Von Thünen's model [55].

Forested land would be most suitable further outside the urban center, and there is a lower suitability for this land use in the Southwestern portion of the study area. This could be due to fewer nearby water resources and a slightly higher urban density in this area. Due to limited, coarse-resolution data available for conducting the forest suitability analysis, forest data at a 1 km resolution was down-scaled to 250 m for the purposes of this study. Thus, note that the suitability map for forest in Fig. 5 is coarser than those of agriculture and urban.

For urban land use, the most suitable areas are within the urban center and to the Southwest of the urban center, with a few

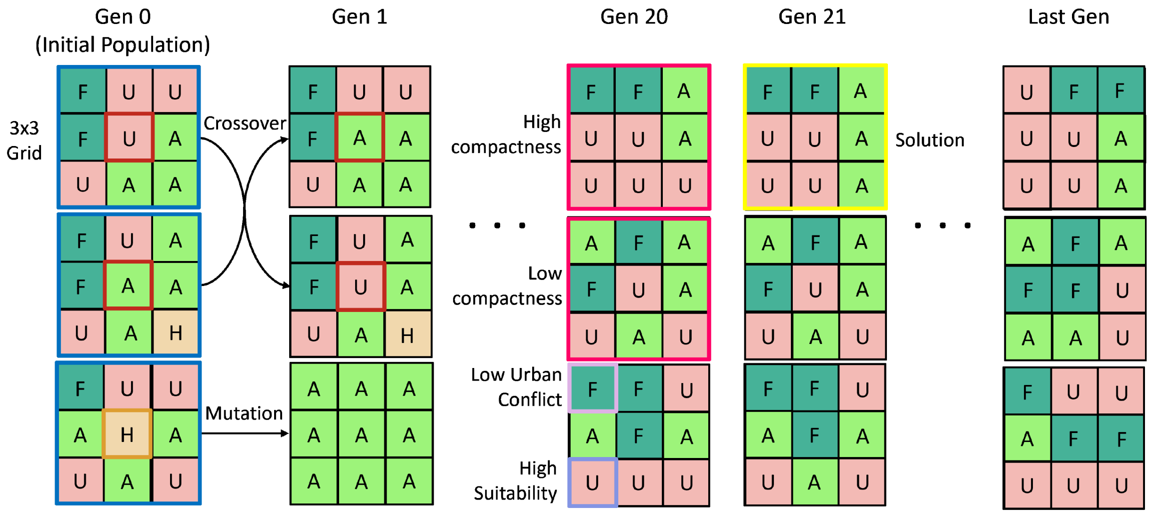

Fig. 4. Example of the GA process used in the study, following a similar algorithm in Wang et al. [30].

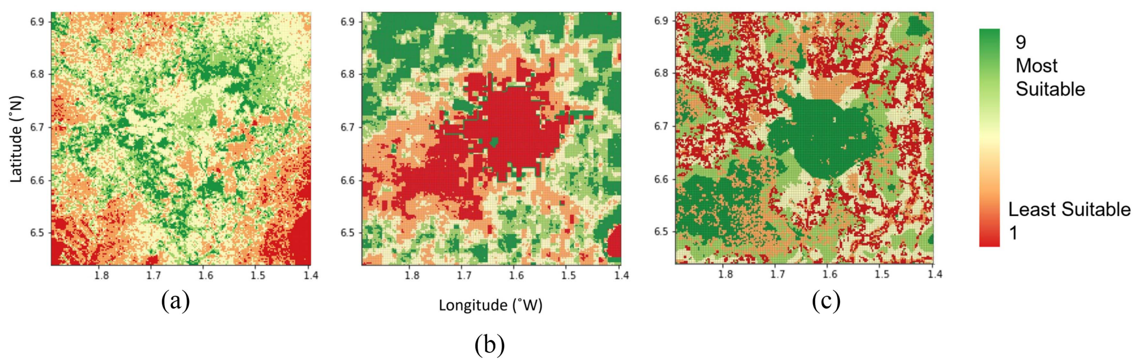

Fig. 5. Results from the land use suitability analyses for (a) agriculture, (b) forest, and (c) urban land uses.

patches of highly suitable areas scattered around the study area. There are smaller human settlements in the land surrounding Kumasi, which could explain the scattered nature of some high-suitability areas [27], [56].

The suitability analyses conducted in this study were based on a simplified set of criteria due to a scarcity of datasets concerning extensive details about the land use in the study area. A comprehensive assessment of land use suitability should include additional subcriteria that affect the suitability of each respective land use type. For example, urban suitability should account for a given land unit's suitability for residential, commercial, industrial, and other uses generally considered "urban." There is also a need for more conservation criteria to provide insights into finer-scale forest suitability levels. High-resolution forest coverage data, including species distribution and biomass measures, as well as water resource boundaries would help to improve the forest suitability models. For the agricultural suitability analysis, the biophysical data provide important information on agricultural productivity influences, such as nutrient availability and water extraction, but additional soil information, such as lime, gypsum, and salinity, could supplement this study to provide further insight into soil structure, nutrient uptake, and crop yield [22], [46], [57]. However, the analyses conducted within this study did include major influences that drive the urban development, such as population density and proximity to existing human settlements.

B. RS Time Series

The slopes output by this process were positive 0.0038 for agriculture, negative 0.0020 for forest, positive 0.0103 for urban, and positive 0.0072 for herbaceous. The p-values of these slopes were all 0, indicating a statistically significant relationship between the change in land use and the change in LST. As expected, the relationship between urbanization and LST was determined to be positive. This finding supported by many studies on UHIs, which have significant impacts on social and environmental conditions in urban centers [16], [17], [28], [58], [59]. The correlation between forested land use change and change in LST was negative, which is supported by studies on forest cooling effects [15], [16], [18]. The correlation with LST change was positive for both agriculture and herbaceous, which could be the result of a combination of factors.

Although it would be expected that agricultural and herbaceous areas would behave in a similar manner to forest, the seasonality of these types of vegetation means that there are certain times of year during, which they act as barren land with increased reflectivity and increased correlations with LST [15],

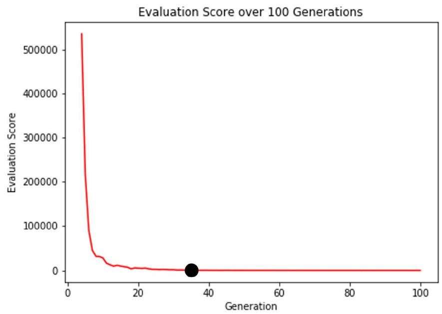

Fig. 6. Convergence in scores of the GA over 100 generations.

[17], [18], [60]. In addition, agricultural systems involving irrigation experience evaporative cooling and thus tend to have lower temperatures, but the areas in the study region are generally rain-fed and lack this cooling effect [60], [61]. It is also important to note that herbaceous and agricultural land areas can present similar characteristics, especially during the crop growth period, which can result in misclassification errors between the land uses [62], because a land classification data source was applied to determine these LST-land use relationships, this potential misclassification could also have impacted the accuracy of the correlations with agriculture and herbaceous lands. The use of one mean LST value for each year in the study period also limits the specificity and accuracy of the relationship between the trends of LST and each land use type. It only provides general LST information across the study region and period that does not investigate the individual pixel LST trends occurring in conjunction with land use change. Despite these potential discrepancies, the relationships found between LST and each land use type demonstrate the importance of RS time series data in uncovering applicable trends to LUP that may otherwise be absent from decision criteria.

C. Genetic Algorithm

For each 2050 land use scenario result, the evaluation score of the original land use decreased significantly when the result was achieved by the GA, indicating that this method effectively addressed the given constraints and objectives of the scenario and provided results with the highest fitness. This decrease can be seen through the convergence of the evaluation score to a minimum over the course of the generations. A typical convergence graph for the algorithm is given in Fig. 6. The convergence point was determined at the generation with a best result that differed by less than 2% from the best result of the final generation. For each scenario, the algorithm converged around generation 35, so this is the number of generations used in study. For 35 generations, the algorithm ran on 8 cores in parallel and output the land use result after about 9 min.

The results for CTS exemplify a potential 2050 land use distribution to accommodate an additional 1 million people if current land use allocation trends are followed, which prioritize urban expansion without consideration for climate effects. A comparison of the original land use and the GA result for CTS are given in Fig. 7(a) and (b). From the original land use distribution to the result, 8.9% of pixels were converted into a different land use type [see Fig. 7(c)]. Most of the changes occurred on the periphery of the urban center, which is expected due to the tendency of urban expansion to occur on the borders of existing urban areas [6], [27], [56]. There are small parcels of urban lands, predominantly scattered throughout the Southern section of the study area, which could be due to the higher original amount of herbaceous pixels in this area that were available to be converted into other land uses. In specifically the Southwestern part of the result, the added urban pixels may be due to a higher urban suitability in the area that encouraged some of the forested lands to be converted. The number of pixels of each land use for the original system and the CTS result are given in Table II, which reveals that agriculture and urban land uses increased significantly, whereas forested areas decreased slightly and herbaceous land decreased significantly. This follows expectations for the scenario, as agricultural and urban lands are designated to be insufficient in the mutation process, and urbanization is also encouraged by the population growth constraint. Although forest land use is also insufficient, and thus prioritized in the mutation function, the lack of the LST constraint results in forested pixels often being overtaken by urbanization. Agriculture is also highly suitable for peri-urban lands, which explains the conversion of forested areas surrounding the urban center into agriculture [55]. The herbaceous pixels experienced a significant decrease due to this LC being the excess designation in the mutation function, and thus many of these lands were converted into the insufficient land use types. This result was able to successfully address the population constraint and 2050 population growth estimation of 1 000 000 people, with urban allocation resulting in the accommodation of 1 000 244 people. The LST increase within the CTS result, calculated through the LST-land use slopes derived from RS time series data, is 7.4°C due to there existing no limitation on this aspect. An increase of this magnitude is undesirable due to the negative impacts of significant LST increases on human and environmental health [13], [15], [17], [18]. This indicates that changes to current LUP practices are necessary for successful and sustainable urban expansion.

TABLE II
LAND USES FOR THE ORIGINAL DISTRIBUTION AND CTS, CAS, AND HDS RESULTS

Scenario	Agriculture	Forest	Urban	Water	Herbaceous
Current	1664	26 121	8494	305	2224
CTS	1908	25 880	10 440	305	275
CAS	1270	26 737	10 440	305	56
HDS	2045	26 096	9387	305	975

The CAS provides a potential land use system for 2050 that also accommodates 1 million people but limits LST increases. The CAS result, as compared with the original land use individual, is given in Fig. 8(a) and (b). The land use changes that occurred from the original land use distribution to the result, which included 8.6% of the study area pixels, are shown in Fig. 8(c). The majority of urbanization occurred in the Southwestern portion of the study area, which is where urban suitability is fairly high. As expected, the changes also seem to largely be located around the periphery of the city center [6], [27], [56].

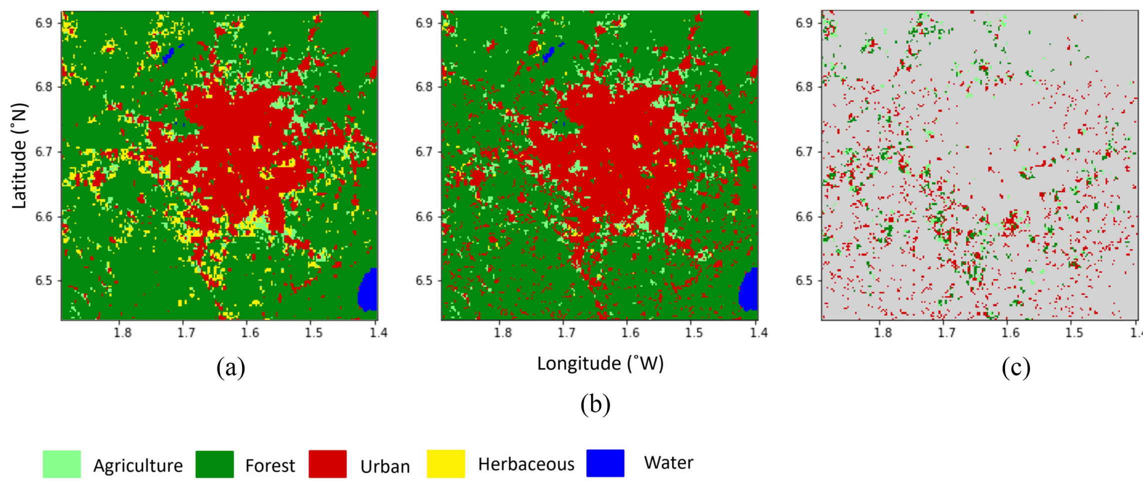

Fig. 7. CTS results: (a) the original land use distribution in Ghana, (b) CTS result for 2050, and (c) pixels that changed, with the color representing the land use type they changed to.

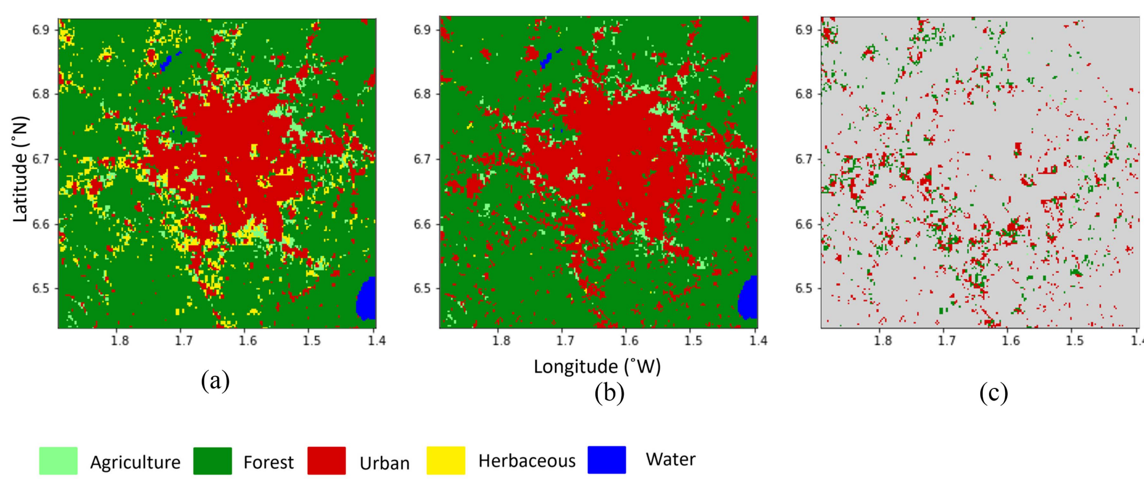

Fig. 8. CAS results: (a) original land use distribution in Ghana, (b) CAS result for 2050, and (c) pixels that changed, with the color representing the land use type they changed to.

The CAS result is able to successfully address the given set of constraints and objectives, with an additional 1 000 244 people accommodated and an LST increase of 1.7°C. It can be seen in Table II that forested areas increased slightly, agricultural and herbaceous areas decreased significantly, and urban areas increased significantly in this result. These patterns represent the combined effects of the mutation function prioritizing agriculture, forest, and urban lands over herbaceous, the population constraint encouraging urbanization, and the temperature constraint assigning higher importance to the forest land use. Agriculture decreased because, although it was insufficient in the mutation process, its positive association with LST prevented it from being prioritized by the algorithm, and thus it was partially overtaken by forested and urban lands. It is common for urban expansion to overtake agricultural areas and for urban centers to import agricultural products from surrounding areas, but losing peri-urban agricultural land often has negative implications in the economic, social, and environmental sectors [63], [64]. In addition, the herbaceous lands, which are most suitable to be converted to agriculture, forest, or urban, are almost depleted in this result. This leaves little room for future urban expansion within the given area without sacrificing the forested and remaining agricultural lands. Despite the success of the CAS result in achieving the given constraints, it reveals several potential issues in terms of decreased agricultural and herbaceous lands that could impact the future development of the Kumasi area.

The HDS for 2050 addresses the same constraints as the CAS, but it includes high density urban expansion to allow for more people to be accommodated within fewer urban pixels, thus allowing for more flexibility in future expansion and land use changes. The original land use distribution and the HDS result, along with the land use changes (5% of pixels) that occurred between them, are given in Fig. 9(a)–(c). Relatively less land use change occurred for this scenario because of the high density urban pixels necessitating less land area for urban expansion. It can be seen that most of the change occurred in the Southern portion of the study area, following common urban expansion trends with most of the urbanization concentrated

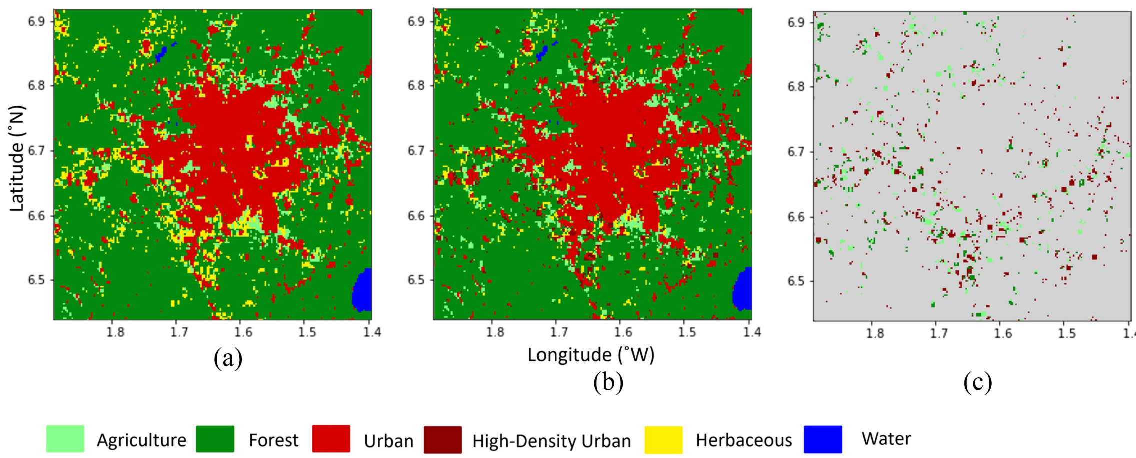

Fig. 9. HDS results: (a) the original land use distribution in Ghana, (b) HDS result for 2050, and (c) pixels that changed, with the color representing the land use type they changed to.

around the bounds of the city center [6], [27], [56]. In this result, as given in Table II, agriculture increased significantly, forest decreased slightly, herbaceous land decreased significantly, and urban areas increased enough to accommodate 1 000 160 people. Despite a small decrease in forest pixels, the LST increase for this result was 1.7°C, indicating that increasing forested areas was not essential for mitigating climate effects in this HDS. This is most likely due to the addition of far fewer urban pixels than in the results for CTS and CAS. Thus, the HDS result was able to satisfy both of the constraints of the algorithm while adding peri-urban agricultural land. In addition, there remained 975 herbaceous pixels in the HDS result, in which this high density setup could accommodate 1 092 000 additional people. This provides future routes for further urban expansion that would not overtake agriculture or forest lands.

There are limitations on the extent to which the GA can adhere to the given constraints while also providing an ideal land use result for all affected parties. While the CAS was able to achieve both the population and LST constraint, agricultural land decreased, which could negatively affect those who depend on employment and resources from these lands. In the HDS, agricultural land increased and both constraints were met, but forested lands experienced a slight loss. Although minimal, losses in forest ecosystems are detrimental to biodiversity and soil health, and many forests in Ghana are already vulnerable due to mining, logging, and agricultural expansion [5], [8], [65], [66]. The relatively small study area and strict constraints and objectives most likely compound the issue of competing land use priorities, but this is ultimately a universal LUP issue that must be assessed by stakeholders to determine the priorities for a particular area.

In all three scenario results, it can be seen that the gridded mutation operation resulted in some of the areas converted to urban to be square land units in their respective results. The mutation operation was able to successfully increase urban compactness and add urban areas closer to the city center, but this tendency for square urban patches in the periphery is not a realistic representation of LUP practices. However, this urban distribution does provide insight into the potential locations for urban expansion within the study region.

In this study, the population density of urban expansion was assumed to be either medium or high across the study area, depending on the scenario. In future work, a wider range of densities could be included within the GA, especially in terms of urban location with respect to the city center. In the center, it is probable that there will be more people accommodated into a smaller area, and vice versa for the peripheral areas, so this could be accounted for by implementing a system to prioritize high density urban development closer to the center or the urban area and medium or low density in the more peripheral areas. Another limitation to the method presented is its computational intensity, as HPC and parallelization were necessary for the algorithm to complete 35 generations in under 10 min. To be able to provide this method as a tool for land use planners and stakeholders, it must be accessible within their computational and time constraints. In addition, for this study, areas classified as water in the original land use distribution were maintained as such throughout the land use evolution. It was assumed that water bodies would remain constant across time, but this could be further studied through exploring how areas may become inundated over time. Remotely-sensed data could be highly informative on this front, as drainage, flood risk, and soil condition could provide potential zones that may become drier or wetter over time. These factors could also be applied to the suitability analysis for a more comprehensive assessment.

We considered only the LST-land use relationships through RS time series data because the UHI effect is a significant issue as development continues in the Kumasi area [28]. The method outlined by this study can be applied to LUP in areas with differing priorities or concerns, as various RS data can be integrated into the analysis based on its significance to these planning priorities. RS metrics, such as evapotranspiration or vegetation indices, could be incorporated into GAs focused on LUP for agricultural efficiency or biodiversity [50], [65], [67].

In future work, the objectives of the algorithm could also be adapted to accommodate varying costs for the replacement of different land use types. In this case, each land use change occurs randomly under crossover and mutation, and there is no direct measure of the conversion cost between land use types. Implementation of a land use conversion cost matrix would allow for a higher level of user input into the algorithm, dictating which land use changes are more or less viable for a particular area [29], [51]. This requires extensive knowledge of the environmental and social characteristics of the study area, but it would provide more guidance for the algorithm.

Overall, this algorithm provides flexibility for LUP purposes depending on the context and goals of an area. It is adaptable to conform to the needs of the scenario being addressed, which may include changing certain parameters to provide more realistic results. In this case, the mutation and crossover probabilities were tested at different values to identify the most applicable combination for the given situation, but other studies on LUP with GAs have applied both lower and higher values for these measures with success [29], [51]. The adaptability of the GA requires extensive knowledge of the LUP goals and limitations for a study area, but it also allows for a customized system that can optimize under a set of constraints, objectives, and parameters specifically tailored to provide the best and most realistic results. subsequently a more realistic result.

A key component of this application of a RS- and suitability-based GA for LUP was climate change mitigation. Because population growth and subsequent urban expansion is heavily associated with increasing temperatures, such as with the UHI effect, it is essential to consider how LUP can either contribute to or dim the impacts of climate change on both human prosperity and environmental conditions [17], [58], [59]. The results of this study are significant because they can be an effective tool to be applied by stakeholders in LUP. The scenario results can provide bases for decision making, upon which stakeholders can input their priorities and adjust to the specific needs of the area of focus. Overall, the GA is able to integrate the RS and suitability modeling aspects of this analysis to create land use maps that could then be used to inform decisions.

IV. Conclusion

The GA was implemented under general, globally applicable assumptions of suitability and land use prioritization. The objectives and constraints, as well as the land use prioritization within the mutation process, were designed to represent broad interests applicable to most areas undergoing urbanization. The city of Kumasi, Ghana, served as a case study for the application of this integration of RS and suitability analysis into LUP, and the outcome includes results for three land use scenarios that provide guidance, which stakeholders can customize to localized concerns and practices. The CTS, CAS, and HDS each were able to accommodate the additional projected 1 000 000 people by 2050. However, LST increases were projected to be much higher if the current land use allocation trajectory is followed (7.4°C), while the scenarios that considered climate effects as a constraint were each able to achieve LST increases below 2°C. The results of this study demonstrate that the GA serves as a tool to effectively apply remotely sensed time series information and suitability models to land use scenario optimization under a combination of constraints of population growth and LST increase mitigation as well as varying population densities. The GA can be used as a tool for exploratory scenario planning, which provides plausible future land use allocations based on trends. This integration of RS data into exploratory scenario planning allows for the long-term impacts of LUP decisions to be better understood, especially in data-sparse regions. Overall, RS offers a novel method for optimizing land use decisions through integration with land use suitability models. In general, this study establishes a foundation for many avenues, in which RS time series data can be applied in conjunction with land use suitability analyses to inform LUP decision making.

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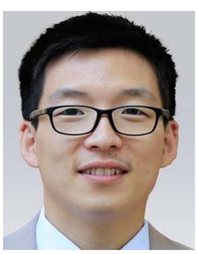
Julie A. Peeling (Graduate Student Member, IEEE) received the B.S. degree in biological engineering from the University of Florida, Gainesville, FL, USA in 2023. She is currently working toward the Ph.D. degree in natural resources and the environment with the Department of Natural Resources and the Environment, Cornell University, Ithaca, NY, USA.

Her research interests include remote sensing applications for environmental management, computational approaches to ecosystem dynamics, and remote sensing time series analysis.



Changjie Chen received the M.Stat. and Ph.D. degrees in design, construction, and planning from the University of Florida, Gainesville, FL, USA, in 2019 and 2021, respectively.

His scholarly endeavors are centered on spatial decision analysis aimed at enhancing the sustainability of urban built environments and bolstering community resilience. The core of his work involves modeling and analyzing integrated systems of land use and transportation, which is achieved through utilizing an agglomeration of technologies, such as geographic information systems, remote sensing, spatial econometrics, machine learning, and high-performance computing.

His research interests to advance urban planning by employing leading-edge geospatial analytics and web-based 3-D graphics technologies to create urban digital twins, offering a dynamic platform to visualize real-world conditions and explore alternative future scenarios.

Jasmeet Judge (Senior Member, IEEE) received the Ph.D. degree in electrical engineering and atmospheric, oceanic, and space sciences from the University of Michigan, Ann Arbor, MI, USA, in 1999.

She is a Professor with the Department of Agricultural and Biological Engineering, Institute of Food and Agricultural Sciences, University of Florida, Gainesville, FL, USA, where she is also the Director of the Center for Remote Sensing. Her research interests include remote sensing, machine learning in agriculture, retrieval algorithms, and spatio-temporal scaling of remotely sensed observations in diverse landscapes.

Dr. Judge is the past Vice-Chair and Chair of the National Academies of Sciences' Committee on Radio Frequencies (2012–2017) and is a Member of the NASA Earth Science Advisory Committee since 2018. She was the recipient of the NASA Group Achievement Award for her contributions to the leading interdisciplinary field campaigns.

Aditya Singh received the M.S. degree in wildlife ecology and conservation from the University of Florida, Gainesville, FL, USA, in 2008 and the Ph.D. degree in forestry from the University of Wisconsin-Madison, Madison, WI, USA, in 2014.

He is a Research and Extension faculty with the Department of Agricultural and Biological Engineering, University of Florida. Broadly trained as a landscape ecologist, his research interests include developing remote sensing-based tools and techniques for assessing landscape structure, composition, and function with a focus on land and water resource conservation.

Silas Achidago received the B.S. degree in human settlement planning from the Kwame Nkrumah University of Science and Technology, Kumasi, Ghana in 2015 and the M.S. degree in geographic information science from the University of Ghana, Accra, Ghana in 2021. He is currently working toward the M.U.R.P (Masters in Urban and Regional Planning) degree with a concentration in GIS with the University of Florida, Gainesville, FL, USA.

His research interests include land use conflicts, land use modeling and automation, and coastal resilience planning.

Alexander Eide received the B.A. degree in sustainability and the M.U.R.P (Masters of Urban and Regional Planning) degree with a concentration in GIS from the University of Florida, Gainesville, FL, USA in 2020 and 2022, respectively.

He is a transportation planner in Miami, FL, USA.

Katelyn Tarrio received the B.A. degree in environmental science in 2017 and the M.A. degree in remote sensing and geospatial sciences in 2018 from Boston University, Boston, MA, USA, where she is currently working toward the Ph.D. degree in earth and the environment.

She studies the use of optical and radar remote sensing to characterize commodity-driven forest loss in the tropics, with a focus on agroforestry systems and tree crops.

Pontus Olofsson received the Ph.D. degree in physical geography from Lund University, Lund, Sweden in 2007.

He is a Research Scientist with NASA Marshall Space Flight Center, Huntsville, AL, USA. Before joining NASA, he was a research Professor and Lecturer with the department of Earth and Environment, Boston University, Boston, MA, USA. His primary research interests include the mining of archives of satellite data to further the understanding of how Earth is changing and the impact of change on people and environment, which also include how to combine remote sensing data and traditional sampling techniques to gain knowledge of environmental change.

Dr. Olofsson is a Science Team Member of the NASA Carbon Monitoring System, the NASA Land-Cover and Land-Use Change Program and NASA SERVIR. He has supported the capacity building efforts of SilvaCarbon for almost a decade.