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Applications of Urban Land Evaluation and Site Assessment (uLESA) in Chesterfield County, Virginia

Emily Hastings
Virginia Commonwealth University

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Abstract

Urban and suburban agriculture is increasing in popularity across the United States. However, many of these farms are short-lived due to a combination of human factors (e.g., managerial, economic, cultural) and environmental or spatial factors (e.g., zoning, soil quality, distance to markets). Geospatial analysis, in the form of suitability modeling, could aid in locating suitable sites for these activities. Land Evaluation and Site Assessment (LESA) is a suitability modeling technique that generates a score for agricultural land use in traditionally rural spaces. This research explores adapting this method to encompass the complexities of placing diverse, in-ground agriculture in urban and suburban areas in Chesterfield County, Virginia and is referred to as Urban Land Evaluation and Site Assessment (uLESA). The uLESA model was developed collaboratively with officials from six departments of Chesterfield County. A total of 20 factors related to natural and agricultural resources, equity and accessibility, and heat island mitigation emerged. An individual scoring criterion was developed for each factor based on its suitability for agriculture and equitable access to agriculture. The final scores generated represented percent suitability for agriculture in urban and suburban spaces. The majority of high percent suitable sites were located within five miles of the border of the City of Richmond, Virginia and the City of Petersburg, Virginia, which are rapidly urbanizing. This underscores the importance of using the uLESA model to inform future planning decisions to conserve these agricultural resources into the future. The uLESA model allows localities to approach localized food system development with greater intentionality and to expand definitions of green infrastructure to include urban and suburban agriculture.

Introduction

Urban and suburban agriculture is becoming increasingly popular and common across the United States (McClintock et al., 2018; Palmer, 2018; Siegner et al., 2018). These operations have the potential to provide economic, environmental, and social benefits to the community, such as increased access to healthy food and reduction in the heat island effect (Ackerman, 2014; Qiu, 2013; Specht et al., 2021). Despite these positive attributes, local governments often respond to (sub)urban agricultural development without clear intentionality, which may set up these farms for failure. Many of these decisions are on a more reactionary basis instead of a strategic one and the resulting site frequently lacks the essential infrastructure and physical conditions for successful agriculture (Jones, 2018; Emas & Jones, 2021). However, a majority of localities do not have the tools or awareness to strategically plan for (sub)urban agriculture, so there is a large hurdle in knowledge and practice to overcome (Lawson, 2004).

This research sought to create an exploratory, collaborative model to locate areas that are ideal for urban and suburban agriculture within Chesterfield County, Virginia to help inform planning decisions. Chesterfield County is located in Central Virginia just south of the City of Richmond and northwest of the City of Petersburg. The County is rapidly urbanizing around both of these bordering Cities, making it the fastest growing locality within the Greater Richmond Area (Chesterfield County, 2020). This locality was chosen due to this rapid growth rate and it being a historically agricultural area since the County was founded in 1749 (Hodges, 1978). This research was participatory, involving County officials from six departments over the course of three years, in order to create a usable tool to inform comprehensive planning decisions.

Urban agriculture encompasses many different agricultural practices. Urban agriculture is generally defined as the practice of cultivating, processing and distributing food within urban areas (Deelstra et al., 2012; Mougeot, 2000; Smit et al., 1996). Urban agriculture can take many forms including non-commercial operations (i.e. school and community gardens) and commercial enterprises (e.g. Community Supported Agriculture farms) (Jones, 2018; Speckt et al., 2021). Urban agriculture typically occupies smaller footprints compared to traditional rural agriculture because it is often constrained by land use policies, zoning regulations, and more limited access to land (Mougeot, 2000). Essential structures for successful urban agriculture may include hoophouses, or structures covered with plastic film for extending the growing season and seed starting, and wash stations, for washing and processing produce to ensure food safety standards (Masson-Minock, 2016).

Within the context of this research, urban agriculture encompasses agriculture that is in-ground, or in raised garden beds, outdoors that supports diverse vegetable production, with crops of many different types, as opposed to a monoculture of one crop type typically found in rural agriculture. Examples of the types of crops grown in diverse vegetable production include nightshades (e.g., tomatoes, eggplants, peppers, potatoes), brassicas (e.g. kale, cabbage, broccoli), fruits (e.g., berry bushes and fruit trees), and legumes (e.g. beans and peas). This research also excludes forms of indoor, controlled environment agriculture (e.g., aeroponic, hydroponic, aquaponic), as well as agriculture occurring on top of a structure (i.e. rooftop farming).

Dynamics of (Sub)urban Agriculture

Urban and suburban agriculture has many positive socio-economic and environmental characteristics. Scholars and practitioners view urban and suburban agriculture as a mechanism to increase access to healthy foods in communities (Badami, 2015). This may be especially true in lower income areas lacking grocery stores and other food establishments to obtain affordable, healthy food (Walker, 2010). The placement of urban agriculture in vulnerable neighborhoods could increase potential access points to healthy food and may start to address an underlying factor of community-level food insecurity (USDA, 2021).

Urban agriculture can also bolster local food systems. Local food systems are thought of as a collaborative network of producers, distributors, processors, retailers, and consumers that is concerned with enhancing food quality, promoting sustainable practices, and supporting local economies within a particular geographic region (Martinez, 2010). Urban agriculture strengthens the local food system by increasing access to fresh, high quality foods for consumers and also increases local food security, as areas across the world are experiencing extreme weather events that negatively impact agriculture (EPA, 2015). Local urban agriculture mitigates against the impacts of food shortages and disrupted supply chains by providing a reliable source of fresh produce that is not dependent on long distance transportation and distribution networks (Béné, 2020). This builds resilient communities that are resilient to domestic and global food shocks if weather-related food shortages continue.

Urban agriculture may have the potential to help mitigate climate change. One of the largest emerging climate issues in cities is the heat island effect, which is when impervious surfaces (i.e. buildings, asphalt, concrete) absorb and store large amounts of heat increasing the local ambient temperature (Deilami, 2018). This increase in temperature can increase heat related illnesses during the heat of summer, exacerbate existing respiratory illnesses (i.e. asthma, COPD), and worsen air quality (Heaviside, 2017). By conserving or adding trees, shrubs, and other perennials in urban areas as greenspace, these plants can decrease temperatures through plant evapotranspiration and improve air quality by the uptake of harmful pollutants by plants through photosynthesis or absorption through leaf pores and plant surfaces (EPA, 2020; EPA, 2022). Examples exist of urban agriculture functioning as green infrastructure across the country (Cohen & Wijsman, 2014; Evans et al., 2022; Tóth & Timpe, 2017). Urban agriculture can function as green infrastructure if utilized with tree and perennial plantings, which can effectively absorb solar radiation compared to bare ground, and thus mitigating against the immediate impacts of the heat island effect (Evans et al., 2022).

Urban agriculture could also serve as a land use and green infrastructure planning tool to create policies to promote urban climate resiliency and equity into the future. However, local governments often do not have the tools and knowledge required to intentionally plan for urban agriculture as green infrastructure (Emas & Jones, 2021; Jones, 2018; Lawson, 2004). Chesterfield County continues to rapidly develop and urbanize creating a pressing need for land use policies to ensure that communities have access to valuable agricultural and green infrastructure resources. However, there is very little data available at the depth necessary to inform such policies. This research is a collaborative effort with Chesterfield County to fill those gaps by creating a scalable and adaptable tool to identify sites most suitable for urban and suburban agriculture with the potential to also mitigate against the negative impacts of the heat island effect.

Introduction to Land Evaluation and Site Assessment

Land evaluation and Site Assessment (LESA) is a geospatial land use tool traditionally used to locate areas of agricultural importance in a rural context (USDA, 2011). This tool is used to assess land by factors such as soil type, land capability, and aesthetic factors to determine its relative agricultural importance (Steiner et al., 1987). It was developed by the Soil Conservation Service (SCS), now the Natural Resources Conservation Service (NRCS), to create an objective system to evaluate land that is under consideration for conversion from farmland to another use (USDA-SCS, 1987). It was originally used to quantify the impacts of federal policies on farmland conversion but has since been utilized by local and state governments to inform land use policies and conserve prime agricultural land (Hoobler et al., 2003; Steiner et al., 1987; Tyler et al., 1987; USDA-NRCS, 2011).

In the early 2000s, scientists began to consider the combination of geographic information systems (GIS) and the LESA system to create a more replicable and detailed assessment for agricultural land suitability (Hoobler er al., 2003). GIS is a computer system for "capturing, storing, checking, and displaying data related to positions on Earth's surface" (National Geographic, 2022). The software allows for suitability modeling using a set of criteria to locate the best locations for a particular activity (ESRI, 2023). GIS is used with LESA to analyze data about the physical characteristics of a particular area, such as topography and soil quality (Dung & Sugumaran, 2005). GIS allows for the integration of multiple datasets through LESA suitability modeling to spatially locate all areas that are suitable for agricultural activities, which can help decision-makers understand these complex relationships and help them to intentionally plan for agriculture.

This research adapted LESA factors into an urban and suburban context, hereafter Urban Land Evaluation and Site Assessment (uLESA), by assessing Chesterfield County across three major categories of factors co-created with County staff: natural and agricultural resources, equity and accessibility, and heat island mitigation. These factors identified locations that a) meet the environmental or spatial needs for successful agriculture, b) are located in areas with low food access and/or in historically underserved communities, and c) are best equipped to mitigate against the heat island effect.

The output from the uLESA model includes a raster cell surface over Chesterfield County with each cell value representing a gradient from least percent suitable to most percent suitable for the intended form of agriculture across the County. The uLESA model can help orient public and private entities towards ideal urban and suburban agricultural sites. In locating these sites, the model has the potential to encourage expansion of urban and suburban agriculture throughout the County and consider its use in long-term green infrastructure planning to benefit Chesterfield residents into the future.

Methods and Materials

Research Objective

The objective of this research was to adapt the Land Evaluation and Site Assessment (LESA) method, originally intended for use in rural agriculture planning, for use in urban and suburban agricultural settings. This required the development of new factors relevant to urban and suburban agricultural settings.

Study Area Description

The study area includes the whole of Chesterfield County, Virginia, which makes up 279,738 acres. Chesterfield County is located in between the Coastal Plain and Piedmont regions of east-central Virginia and is bounded to the north by the City of Richmond and to the southeast by the City of Petersburg (Figure 1). Chesterfield County is the fifth largest county in the state of Virginia. Its population has grown by 15.5% since 2010, as of the 2020 US Census, with much of the growth concentrated around the border of the Cities of Richmond and Petersburg (Chesterfield County, 2020). Currently, the County is consistently ranked among the highest in population growth out of all localities in the Commonwealth of Virginia (Greater Richmond Partnership, 2022). Population growth is projected to increase by approximately 8% between 2020 and 2030 according to the Chesterfield County Strategic Information Sharing (StratIS) model (Chesterfield County, 2023). Chesterfield County was chosen as the study area based on its patterns of rapid population growth and subsequent urbanization, as the Greater Richmond Region continues to expand.

Figure 1: *Chesterfield County, Virginia with the surrounding counties and cities*.

Chesterfield County is considered a historically agricultural area with a large number of equestrian farms (Hodges, 1978). However, development is beginning to expand into these agricultural areas in the southwestern portions of the County (Chesterfield County, 2019). In 2007, 220 farms existed within the County which made up 21,527 acres of land, or 7.7% of the land area of the County, according to the USDA Census of Agriculture (USDA-NASS, 2007). As of 2017, 210 farms existed with a total of 18,013 acres of land, or 6.4% of the land area of the County, which is a 16.3% loss of farmland within the ten-year period (USDA-NASS, 2017). Land use data was available between 2006 and 2016. Within that ten-year period, open space, low intensity, medium intensity, and high intensity development collectively increased by 6.7% from 83,580 acres, or 30% of the County, to 89,174 acres, or 32% of the County. As the population of Chesterfield continues to expand, development continues to expand into agricultural areas along major thoroughfares (Chesterfield County, 2019). To account for this expansion, between 2010 and 2017 the County rezoned approximately 385 acres of land from agricultural to residential zoning designation (2019).

Development of Analysis Factors

Three pillars guided the creation of factors for the uLESA model: the USDA National Agricultural LESA Guidebooks, examination of existing scholarship that speculates on factors encouraging viability of the examined forms of urban agriculture, and input from Chesterfield County officials (Pease & Coughlin, 1996; USDA-SCS, 1983; USDA-NRCS, 2011). Through a collaborative process with County staff, 20 factors emerged as viable for use in the model. Factors aligned with one of three thematic categories: natural and agricultural resources, equity and accessibility, and heat island mitigation (Table 1).

Table 1. *uLESA factors by category.*

Natural & Agricultural Resources	Equity & Accessibility	Heat Island Mitigation
Avoids RPAs & Wetlands	Avoids Targeted Development	Processed Air Temperature
Adjacent to Conserved Land	Permissibility of Produce Sales	
Watershed Impact	Proximity to Bus Stops	
Soil Quality	Walkability	
Adjacent to Existing Greenspace	Proximity to Schools	
County Land Use / Land Cover	Foodshed Score	
Slope	Proximity to Food Providers	
Aspect	Proximity to Other Farms	
Proximity to Contaminated Sites	% Non-White Residents	
Proximity to Existing Water Lines		

The USDA LESA Guidebooks include separate factors for land evaluation and site assessment. In traditional LESA, land evaluation (LE) factors are factors related to soil quality, such as soil type, and site assessment (SA) factors are all other factors not related to the soil, such as development pressure (Pease & Coughlin, 1996; USDA-NRCS, 2011). Given the complexities of the desired forms of agriculture in urban and suburban environments, this distinction was less relevant and was dropped in favor of the three themes. However, these factors guided the selection of factors for uLESA.

A review of scholarship of the spatial, socio-economical, environmental, and site-based characteristics that can encourage viability of the examined types of urban and suburban agriculture revealed an incomplete picture of what conditions lead to successful agriculture in this context. In many cases, factors that might encourage viability are mentioned as an afterthought or without empirical testing. For example, in McClintock and Cooper's (2010) analysis of public land for urban agriculture in Oakland, CA land slope below 30% is noted as desirable without specific reference to empirical testing of this assertion. In some cases, such claims might be seen as self-evident (i.e. community gardens likely cannot succeed on 30% slope or greater). When available, existing scholarship guided the selection of, and development of scoring systems for, the factors used in this research.

Chesterfield officials were instrumental in co-creating the uLESA model. Officials from six departments participated: Parks and Recreation, Planning, Economic Development, Environmental Engineering, Community Development, and Cooperative Extension Service. Their involvement occurred in several stages from 2020-2022. Informal meetings with staff in late 2020 briefed staff about the project and solicited initial perceptions about the selection of factors. Whenever possible, staff with specific subject area expertise guided the creation of factors relevant to that expertise. Meetings during 2021 focused on how to align available data with the selection of factors. Meetings throughout 2022 briefed staff on the progress of the analysis, and to solicit feedback on preliminary findings.

Data Sources

Geospatial data was collected from several governmental and non-governmental sources to create the uLESA model (Table 3). Federal datasets included the Environmental Protection Agency (EPA) Resource Conservation and Recovery Act (RCRA) database, the EPA National Walkability Index, the United States Geological Survey (USGS) 3DEP dataset, the Multi-Resolution Land Characteristics (MRLC) Consortium's National Land Cover Database, and the

US Census Bureau’s 2020 census data and American Community Survey (ACS) data. State datasets included the VDCR floodplains dataset, the VDCR Watershed Impact Model, the Virginia ConservationVision Agricultural Model, and the VDCR Resource Protection Areas (RPA) dataset. Chesterfield County datasets included waterline locations, conservation and open space easements, development nodes from the 2019 Chesterfield Comprehensive Plan, zoning maps and policies, bus stop locations, County and State parks, and public-school locations. Other datasets included internal Virginia Commonwealth University (VCU) food provider location data and regional Heat Island Effect data from the Science Museum of Virginia.

Table 3. *Data sources by uLESA factor.*

No.	Factor	Data Source	Year Data Published
1	Avoids RPAs & Wetlands	EPA, DEQ, VDCR	2022
2	Adjacent to Conserved Land	County GIS, VDCR (Conservation Easements)	2022
3	Watershed Impact	VDCR (Watershed Impact Model)	2022
4	Soil Quality	VDCR (Agricultural Model)	2015
5	Adjacent to Existing Greenspace	County GIS, VDCR	2022
6	County Land Use / Land Cover	National Land Cover Database	2019
7	Slope	USGS (3DEP)	2022
8	Aspect	USGS (3DEP)	2022
9	Proximity to Contaminated Sites	EPA	2022
10	Proximity to Existing Water Lines	City of Richmond Public Utilities	2020
11	Avoids Targeted Development	Chesterfield Comprehensive Plan	2018
12	Permissibility of Produce Sales	County Zoning Information	2022
13	Proximity to Bus Stops	GRTC Transit System	2022
14	Walkability	EPA (National Walkability Index)	2021
15	Proximity to Schools	County GIS	2022
16	Foodshed Score	VDCR (Agricultural Model)	2015
17	Proximity to Food Providers	Center for Urban and Regional Analysis at VCU	2022
18	Proximity to Other Farms	County GIS (Zoning Maps)	2022
19	% Non-White Residents	US Census	2020
20	Processed Air Temperature	Science Museum of Virginia	2022

Geospatial Analysis and Factor Scoring

Geospatial data layers were created for each of the 20 uLESA factors in the ArcGIS Pro Software. All layers were projected to the Lambert Conformal Conic projection with the Virginia State Plane South coordinate system (FIPS Code 4502). The map units were in US Survey Feet. The data were scored based on the combined environmental and biophysical characteristics with County input and rasterized or resampled to a 500-foot resolution to be combined in Raster Calculator to build the final uLESA suitability model. Due to the large size of the County and software processing capabilities, the modeled raster data layers were created with a resolution of 500 feet, or approximately 5.7 acres.

Each input model factor had a potential maximum score of ten based off of the USDA LESA Guidebook recommendations. The analysis included both inclusionary and exclusionary factors to ensure that elements that increased agricultural viability were scored highly and elements that make agriculture impossible or would negatively impact agricultural viability were removed from the analysis. Each exclusionary factor could award -9999 points if the exclusionary condition was triggered, an arbitrary negative score sufficient to remove that cell from potential suitability. Each factor could receive a weight from one to three based on input from County officials and the factor’s environmental, equity, and agricultural implications for the County. This could potentially increase the highest potential score of a single factor to 30 points.

Natural & Agricultural Resource Factors

Avoids Resource Protection Areas, Wetlands, and Floodplains

This factor is an exclusionary factor, as wetlands and floodplains are frequently wet and, therefore, unsuitable for agriculture. These elements and Resource Protection Areas (RPAs) also encompass ecologically fragile systems that have water quality implications (Virginia Administrative Code, 2015). These areas reduce sediment, nutrient, and toxic substance loads in runoff that would otherwise wash directly into the Chesapeake Bay (VDCR, 2007). RPAs require a mandatory 100-foot buffer around this ecological resource, as required by Virginia state law (Virginia Administrative Code, 2015). In the uLESA model, RPAs, wetlands, and floodplain vector polygon layers were buffered by 500 feet, equivalent to the width of one raster cell. A scoring field was created to categorize which areas would be excluded or included in the analysis based on the presence of the buffered polygons. Every polygon within that buffer zone received a score of -9999 to ensure that these areas were properly excluded. This would ensure that no future raster cells containing those resource polygons would be interpolated as suitable due to the minority or lack of the cell area taken up by RPAs, wetlands, and/or floodplains. All other areas outside of the buffered area received a score of 10. The polygons were rasterized to a 500-foot resolution using the scoring field.

Inside Conserved Land

The conserved land factor was used to favor the utilization of existing protected areas, such as conservation and open space easements, for agriculture. This would provide for additional ecological protections on the land, such as riparian buffers and stabilization of fragile soils that are a requirement of conservation easements in Virginia, while also having an active agricultural site (Virginia Department of Forestry, 2021). Every conservation or open space easement is different and not all conservation easements allow for agricultural activities, so further investigation is needed if these sites are identified as ideal for urban agriculture (Virginia Conservation Easement Act, 2016). The data for this layer included open space easements, conservation easements, County Parks, and State Park vector polygons. The data was scored based on being located inside or outside of the buffer. Inside the buffer received a score of ten and outside the buffer received a score of zero. The polygons were rasterized to a 500-foot resolution using the scoring field.

Watershed Impact

The watershed impact factor is an exclusionary factor that utilizes the Virginia Department of Conservation and Recreation's (VDCR) ConservationVision Watershed Impact Model. This raster dataset has a 30-meter resolution. The model's purpose is to identify areas prime for conservation, restoration, or implementation of best management practices that could maintain or improve water quality (VDCR, 2022). The model uses multiple data sources to derive its findings including precipitation, geology, soils, and hydrology. Potential impact is calculated under a "worst case scenario" approach that considers impacts to the watershed if said area was completely barren, therefore it does not consider land cover (2022). This makes the model robust in the face of land cover changes and future development. Watershed impact is scored from 0 – 100% potential impact, with 100% having the most possible negative impact to the surrounding watershed. The raster was reclassified to exclude or include areas based on their potential impact to the watershed. All areas that received a score above 60% of watershed importance were reclassified to have a score of -9999 to be excluded from the analysis. All areas that scored below 59% importance were reclassified to have a score of ten. The 60% threshold was chosen from input from VDCR scientists and because scores above this threshold were considered to have moderate to high potential watershed impact according to the model. The raster dataset was then resampled to a 500-foot resolution.

Soil Quality

The soil quality factor was used to identify prime soils within the uLESA model. This data was taken from the Virginia ConservationVision Agricultural Model vector polygon dataset. This model was developed to quantify the soils suitable for agricultural use. The model was developed with data extracted from the NRCS's Gridded Soil Survey Geographic Database (gSSURGO). The soil quality value was derived by farmland classification, non-irrigated capability class, and National Commodity Crop Productivity Index (VDCR, 2015). The suitability value ranged from zero, or unsuitable, to 100, or optimal. This dataset provides information that was designed to prioritize agricultural land for placement into conservation easements (2015). The vector dataset was classified in five equal intervals to create a consistent, equitable approach to scoring that considers the distribution of data. A scoring field was created to assign a score to each equal interval. Soil suitability values from 0 to 19.9 received a score of zero, values from 20 to 39.9 received a score of four, values from 40 to 59.9 received a score of six, values from 60 to 79.9 received a score of 8, and values from 80 to 100 received a score of 10. The polygons were rasterized to a 500-foot resolution using the scoring field.

Inside/ Adjacent to Existing Greenspace

This factor was used to encourage expanding existing greenspaces and increase connectivity between these areas, which with uLESA model results could favor an agricultural easement being placed on said identified land to conserve it in perpetuity. This could allow for the protection of wildlife habitat in the area and provide for additional ecological protections on the land such as riparian buffers and stabilization of fragile soils that are a requirement of conservation easements in the State of Virginia (Virginia Department of Forestry, 2021). The data included public greenspaces, such as State parks, County Parks, and trails. These vector polygon features were buffered by 500 feet, or one width of a future raster cell. The data was scored based on being located inside or outside of the buffer. Inside the buffer received a score of ten and outside of the buffer received a score of zero. The polygons were rasterized to a 500-foot resolution using the scoring field.

County Land Use/Land Cover

The County land use/land cover factor is an exclusionary factor used to exclude all water bodies, such as rivers, streams, wetlands, and lakes, and impervious surfaces due to these characteristics making agricultural activities either impossible or difficult. The Multi-Resolution Land Characteristics (MRLC) Consortium's National Land Cover Database (NLCD) was used to derive this metric. This dataset has a resolution of 30 meters. The raster dataset was reclassified to exclude areas with a classification of water (11), developed (21-24), and wetlands (90 and 95). All of the areas coded as impervious cover, water bodies, or wetlands were reclassified to have a score of -9999. All other land cover classes were reclassified to have a score of ten. The raster dataset was then resampled to a 500-foot resolution.

Slope

The slope factor is a partial exclusionary factor used to identify high slope areas that would be highly susceptible to runoff and would require extensive land reshaping in order for agriculture to be successful. The USGS 3D Elevation Program, or 3DEP, raster dataset was utilized to derive this factor. This dataset has a resolution of ⅓ arc-second, or approximately 10 meters. The elevation dataset was converted to slope with percent rise units using the Slope tool in ArcGIS Pro Spatial Analyst. Areas with high slopes were to be excluded from the analysis due to the intensive labor required to make it a working agricultural site, such as land terracing. The raster dataset was reclassified so that all slope values above 10% received a score of -9999 to exclude them out of the analysis. Slope values between 5 – 9.9% were reclassified to receive a score of five, as these conditions are not optimal but less intensive land modifications can be completed to make agriculture successful. Values between 0 – 4.9% were reclassified to receive a score of ten, as these areas are most optimal for successful agriculture with little to no modifications needed. The raster dataset was then resampled to a 500-foot resolution.

Aspect

The aspect factor was used to determine the cardinal direction that slopes are facing, as hillsides with southern facing slopes receive more sunlight and are therefore best for agriculture. Most agricultural crops require full sun, which is at least six hours of direct sunlight each day (Almanac, 2023). Eastern facing slopes generally receive mostly morning light and little afternoon light, while western facing slopes generally receive afternoon light with little morning light. Northern facing slopes receive less direct sun exposure than the other cardinal directions and therefore is the least suitable for siting agriculture.

The USGS 3DEP raster dataset was utilized to derive this factor. This dataset has a resolution of ⅓ arc-second, or approximately 10 meters. The ArcGIS Spatial Analyst Aspect tool was utilized to convert the elevation raster to an aspect raster with degree units. The raster was reclassified using breaks determined by the USGS for the cardinal directions. The southern facing slopes between 157.5° - 202.5° were reclassified to have a score of ten. The southeastern facing slopes between 112.5° - 157.5° and southwestern facing slopes between 202.5° - 247.5° were reclassified to have a score of eight. The eastern facing slopes between 67.5° - 112.5° and the western facing slopes between 247.5° - 292.5° were reclassified to have a score of six. The northeastern facing slopes between 22.5° - 67.5° and the northwestern facing slopes between 292.5° - 337.5° were reclassified to have a score of four. The northern facing slopes between 0° - 22.5° were reclassified to have a score of two. The aspect dataset also included water features that did not have an associated aspect and these areas with an assigned value of -1 were reclassified to have a score of zero. The raster dataset was then resampled to a 500-foot resolution.

Proximity to Contaminated Sites

The contaminated sites factor is an exclusionary factor to remove any sites with potential soil contamination, such as heavy metals and petroleum products. The dataset included superfund sites, solid waste facilities, and Toxic Release Inventory (TRI) point locations from the EPA. There are no brownfields located within Chesterfield County. Each of the points were buffered by 0.5 miles. This was to ensure that the whole property was encapsulated and that surrounding contaminated soils or where air pollution may be actively released were excluded. A scoring field was created to prioritize excluding buffered contaminated sites from the analysis. Every area located within the buffer received a score of -9999. This was to minimize the likelihood of agriculture being placed in areas with high potential of soil contamination, which would require produce to undergo extensive food safety measures to minimize the amount of contaminated soil left on produce to ensure the utmost safety. All areas located outside of the buffered area received a score of ten. The polygons were rasterized to a 500-foot resolution using the scoring field.

Proximity to Existing Water Lines

This factor was used to prioritize areas that have relatively accessible water access for agricultural activities, which is essential to successful agricultural production. A water line vector dataset from Chesterfield County was used to derive this factor. Water lines were buffered by 25 feet because the cost of installing a new connecting water line of that length to existing infrastructure would likely be cost prohibitive, with the national average for a 25-foot waterline in 2023 costing approximately $3,750 (Christin, 2023). A scoring field was created so that the buffered water lines could be prioritized. All areas located within the 25-foot buffer received a score of ten, while all other areas received a score of zero. The areas without the buffered water lines were not excluded from the analysis because Chesterfield County has many water bodies and they have the potential to serve as an additional irrigation source according to Virginia water rights on private property (Reavis, 1986). The polygons were rasterized to a 500-foot resolution using the scoring field.

Equity & Accessibility Factors

Avoids Targeted Development

This factor is an exclusionary factor used to avoid key development nodes to maximize the likelihood for extended land tenure, as rapidly developing areas may lead to unstable land tenure for agriculture when property values rise. Chesterfield County did not have geospatial data for targeted development areas so a dataset was built based on development corridors listed in Chesterfield County's Comprehensive Plan and input from County officials. This was approximated by selecting the road segments where major development was happening and buffering these main thoroughfares by 0.5 miles. A scoring field was created to exclude development corridors from the analysis. All areas located within the buffer received a score of -9999 to be excluded out of the analysis. All other areas outside of the buffered area received a score of ten. The polygons were rasterized to a 500-foot resolution using the scoring field.

Permissibility of Produce Sales

This factor was used to determine where current zoning would allow for the sale of produce on a given agricultural site located within that area. This would guarantee at least one secure marketplace for agricultural producers to sell their products. Agriculturally zoned areas were the only areas where code allowed for the sale of produce in Chesterfield County. A zoning vector polygon layer from the County was utilized to derive this factor. A scoring field was created to prioritize areas zoned agricultural. All areas located within agriculturally zoned areas received a score of ten. All other areas received a score of zero. The polygons were rasterized to a 500-foot resolution using the scoring field.

Proximity to Bus Stops

The bus stop factor was used to determine areas located close to public transportation to prioritize accessibility to these sites for people without their own mode of transportation. Vector point data for bus stops was obtained from the Greater Richmond Transit Company (GRTC), which operates within the City of Richmond and Chesterfield County. A multi-ring buffer was created around the 44 bus stops located in the County. These bus stops are located primarily on the border with the City of Richmond and partially down Jefferson Davis Highway, a major thoroughfare, excluding the majority of the County. There were 0.25-mile, 0.5-mile, 0.75-mile, and 1-mile buffers based on the Chesterfield County metric that assets located within 1-mile have walkable accessibility to the average person. A scoring field was created to assign each buffer region a score. The 0.25-mile buffer was located closest to the central bus stop point so it received a score of ten. The 0.5-mile buffer received a score of eight, the 0.75-mile buffer received a score of six, and the 1-mile buffer received a score of four. All other areas located outside of the buffer regions received a score of zero. The buffer polygons were rasterized to a 500-foot resolution using the scoring field.

Walkability

The walkability factor was used to determine areas most walkable within the County to prioritize placing agricultural sites so they are accessible by walking. The US Environmental Protection Agency (EPA) National Walkability Index was utilized, which generates a walkability score based on intersection density, proximity to transit stops, and the mix of employment types by block group. The walkability scores were classified into four quantile groups (EPA, 2022). The range of scores found within the County were one to ten with the average walkability score being two, or least walkable according to the EPA's metric. A scoring field was created to assign each quantile a score. Walkability scores between 15.26 and 20 were considered most walkable and received a score of ten, scores between 10.51 and 15.25 were considered above average walkable and received a score of five, scores between 5.76 and 10.5 were considered below average walkable and received a score of two, and scores between 1 and 5.75 were considered least walkable and received a score of one. The polygons were rasterized to a 500-foot resolution using the scoring field.

Proximity to Schools

The proximity to school factor was used to prioritize placing agricultural sites near public schools for potential educational opportunities. A vector point layer was obtained from

Chesterfield County. Multi-ring buffers were placed around the 66 public schools and technical centers. There were 0.25-mile, 0.5-mile, 0.75-mile, and 1-mile buffers created to provide a site that may be walkable from a given school. A scoring field was created to score the buffer polygons. The 0.25-mile buffer region located closest to the public-school point received a score of ten. The 0.5-mile buffer received a score of eight. The 0.75-mile buffer received a score of six and the 1-mile buffer received a score of four. All other areas located outside of the buffers received a score of zero. The polygons were rasterized to a 500-foot resolution using the scoring field.

Foodshed Score

The foodshed score factor was used to determine the relative ease for producers to get their products to consumers. The VDCR ConservationVision Foodshed Score raster dataset was used for this metric. This dataset has a resolution of 30 meters. VDCR staff utilized data from the 2010 Census, farmers' market locations, road centerlines with speed limits, land cover data, and a representation of urban areas by road density to create a system to quantify the average travel time to markets for farmers (VDCR, 2015). Foodshed scores ranged from 0 to 100 in the County. The raster dataset was reclassified into five equal intervals to create a consistent, equitable approach to scoring that considers the distribution of data. A foodshed score of zero was reclassified to have a score of zero, foodshed scores from 42 to 45 was reclassified to have a score of four, foodshed scores from 46 to 54 was reclassified to have a score of five, foodshed scores from 55 to 65 was reclassified to have a score of six, foodshed scores from 66 to 74 was reclassified to have a score of seven, foodshed scores from 75 to 85 was reclassified to have a score of eight, foodshed scores from 86 to 94 was reclassified to have a score of nine, and foodshed scores from 95 to 100 was reclassified to have a score of ten. The raster dataset was then resampled to a 500-foot resolution.

Proximity to Food Providers

The food provider factor was used to determine areas where there may be limited access to food to mitigate against food desert conditions by prioritizing these areas for agriculture. Food providers are deemed accessible by being within a walkable distance of one-mile of a given population. An unpublished vector point dataset owned by Center for Urban and Regional Analysis at Virginia Commonwealth University was utilized with locations for grocery stores, food pantries, corner stores, convenience stores, gas stations, farmers markets, and other similar data. All food provider points were buffered by one mile. A scoring field was created to score the buffered food provider polygons. The data was scored based on being inside or outside of the buffer. Inside the buffer received a score of ten and outside the buffer received a score of zero. The polygons were rasterized to a 500-foot resolution using the scoring field.

Proximity to Other Farms

This factor prioritized proximity to other farms under the assumption that potentially unknown factors encourage successful, current ongoing agricultural activity, and the additional assumption that clustering of agriculture could allow for sharing of resources. Location data on active agriculture was not available, so agricultural zoned areas were used as a proxy. Zoning polygons were obtained from Chesterfield County. A 0.5-mile buffer was placed around the zoned agricultural areas to also allow for clustering of farms immediately outside this zoning, which consists of more suburbanized residential areas on the border of this zone. A scoring field was created to score the buffer region. All areas located in the buffered zoned agricultural areas received a score of ten and all outside areas received a score of zero. The buffer polygons were rasterized to a 500-foot resolution using the scoring field.

Percent Census Tract Non-White Residents

This factor was used to prioritize equitable access to urban agriculture by scoring areas with higher percentages of non-white residents more highly. This factor serves as a proxy to counteract systemic discrimination against Black Indigenous and People of Color (BIPOC) farmers, as well as encourage green spaces in spaces that historically faced housing discrimination (i.e. redlining) (White, 2018). The Home Owners' Loan Corporation's (HOLC) redlining maps of the City of Richmond did not extend into Chesterfield County. US Census vector polygon data was analyzed by census tract to prioritize these areas (US Census Bureau, 2020). The data was classified into five quantiles. The percentage of non-White residents, excluding White Latinos, was split into five quantile classes with 6.1% to 15.9% receiving a score of two, 16% to 24.3% receiving a score of four, 24.4% to 36.1% receiving a score of six, 36.2% to 50.6% receiving a score of eight, and 50.7% to 92.2% receiving a score of ten. The polygons were rasterized to a 500-foot resolution using the scoring field.

Heat Island Mitigation

Processed Air Temperature

The air temperature factor was used to prioritize areas with the current highest summer temperatures to allow potential agricultural sites to serve as green infrastructure and mitigate against the heat island effect by preventing areas from conversion to impervious surfaces in the future. The processed air temperature raster dataset was obtained from the Science Museum of Virginia (Shandas et al., 2017). This dataset has a resolution of 10 meters. The minimum processed air temperature for Chesterfield County in 2022 was 88° F. The highest processed air temperature was 94.9° F. The air temperatures were classified into equal intervals to score the temperature values from one to ten. Equal intervals were used to create a consistent, equitable approach to scoring that considers the distribution of data. Temperatures from 88.233 - 88.943° F were reclassified to have a score of one, temperatures from 88.944 - 89.312° F were reclassified to have a score of two, temperatures from 89.313 - 89.680° F were reclassified to have a score of three, temperatures from 89.681 - 90.075° F were reclassified to have a score of four, temperatures from 90.076 - 90.444° F were reclassified to have a score of five, temperatures from 90.445 - 90.786° F were reclassified to have a score of six, temperatures from 90.787 - 91.181° F were reclassified to have a score of seven, temperatures from 91.182 - 91.734° F were reclassified to have a score of eight, temperatures from 91.735 - 92.840° F were reclassified to have a score of nine, and temperatures from 92.841 - 94.947° F were reclassified to have a score of ten. The raster dataset was then resampled to a 500-foot resolution.

Factor Weights and Percent Suitability

The uLESA method allows for some factors to be determined as more important, or of greater "weight", than other factors. The uLESA model approaches the weighting system differently than the USDA LESA Guidebook to allow for ease of input from government officials. The traditional LESA weighting system uses a weight range from 0 to 1.00 and mandates that all weights must add up to 1.00 across categories (Pease & Coughlin, 1996; USDA-NRCS, 2011).

The uLESA model considers all factors together from each of the three categories with no weight value limit and each factor can be weighted on a scale of 1x multiplier being important, 2x multiplier being more important, and 3x multiplier being most important to the analysis. This weighting system allowed County officials to vote for factor weights in an asynchronistic manner outside of scheduled meetings. Four factors were weighted with the highest value (i.e. a weight of 3) because of their important environmental, equity, and agricultural implications for the County. These factors included processed air temperature, percent census tract non-White, aspect, and proximity to existing water lines.

Chesterfield officials collaborated in determining the weights of the remaining factors. Across multiple meetings, Chesterfield officials learned about the proposed factors and were then asked to complete a virtual form which surveyed their individual recommended weights. Their weighted scores were averaged together for each separate factor and rounded to the nearest one to determine the final factor weights (Table 2).

Table 2. *uLESA factor weights and maximum scores.*

Factor	Weight	Maximum Score
Avoids RPAs & Wetlands	1	10
Adjacent to Conserved Land	2	20
Watershed Impact	1	10
Soil Quality	2	20
Adjacent to Existing Greenspace	2	20
County Land Use / Land Cover	1	10
Slope	1	10
Aspect *	3	30
Proximity to Contaminated Sites	1	10
Proximity to Existing Water Lines *	3	30
Avoids Targeted Development	1	10
Permissibility of Produce Sales	2	20
Proximity to Bus Stops	2	20
Walkability	2	20
Proximity to Schools	2	20
Foodshed Score	2	20
Proximity to Food Providers	1	10
Proximity to Other Farms	1	10
% Census Tract Non-White Residents *	3	30
Processed Air Temperature *	3	30
Total	**36**	**360**
*indicates factor automatically received a weight of 3		

Final Scoring of Factors: Percent Suitability

Final scoring for the uLESA suitability model used percent suitability as the final metric due to layers having varying scales, from potentially -9999 to ten. The percent suitability score of the raster cells was calculated with Raster Calculator by multiplying each scored layer by their appropriate weight, dividing by the total possible score, and multiplying by 100 to create a percentage. This created an overlay of raster cells with 500-foot resolution over the County that corresponded with the percent suitability for agricultural activities. Any raster cells with a score below 0 (i.e. a cell with at least one exclusionary factor) were excluded from the analysis.

Chesterfield County's parcel layer was overlaid with the uLESA model to identify ownership characteristics of highly suitable land for urban agriculture. This also allowed for publicly-owned versus privately-owned parcels to be identified to orient County officials and the regional land conservancy towards utilization or conservation of those properties.

Results and Discussion

This research was successful in its objective of adapting the Land Evaluation and Site Assessment (LESA) method to identify ideal locations for inground, diverse agriculture in urban and suburban environments. What follows is a summary of results generated by the modeling process, as well as an examination of two case studies of highly suitable sites that were of interest to Chesterfield staff.

The total area of the raster cells completely contained within the County boundary was 275,161 acres (Figure 2). A total of 195,300 acres, or 71% of the study area, were excluded from the analysis by receiving a percent suitability score below a value of zero (Table 4). Low percent suitability scores between 28% - 44% made up 35,750 acres, or 13% of the study area. Medium percent suitability scores between 45 - 59% made up 42,998 acres, or 15.6% of the study area. The highest percent suitability scores between 60 - 75% made up 1,113 acres or 0.4% of the study area. All cells within the 90th percentile of percent suitability, receiving a score of 68% or above, and were located either within five miles of the City of Richmond or the City of Petersburg, which border the County to the north and southeast.

Figure 2. *uLESA Percent Suitability Scoring for Chesterfield County.*

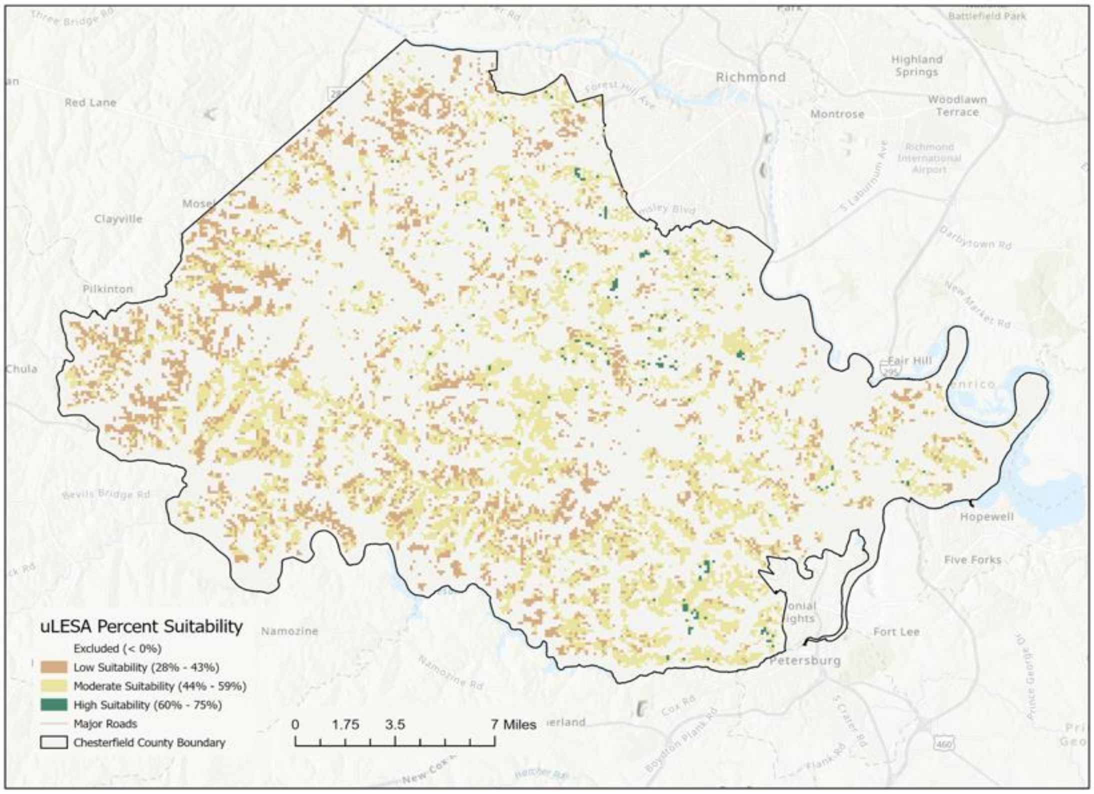


Table 4. *Percent suitability categories with associated area and percent coverage.*

Percent Suitability	Area (acres)	Percent of Study Area
Excluded (≤ 0%)	195,300 acres	71%
Low Suitability (28-43%)	35,750 acres	13%
Moderate Suitability (44-59%)	42,998 acres	15.6%
High Suitability (60-75%)	1,113 acres	0.4%

A total of 28 publicly-owned parcels contained suitability scores within the 90th percentile of scores. Approximately 32% of those parcels were public schools, 39% of the parcels were owned by Virginia State University, 21% of the parcels were directly adjacent to public schools and contained the same high scoring raster cells, and the remaining parcels were the County Fairgrounds and a high school athletic complex (Table 5).

Table 5. *Categories of publicly-owned parcels that scored within the 90th percentile of most suitable for urban agriculture.*

Publicly-Owned Parcel Category	Number of Parcels That Contained a Highly Suitable Score	Percent of Highly Scoring Parcels
Public Schools	9 parcels	32%
Parcels Directly Adjacent to Schools	6 parcels	21%
Virginia State University	11 parcels	39%
Athletic Complex & County Fairgrounds	2 parcels	8%

Public schools and adjacent properties may have scored highly due to a number of factors. Public schools make up 11% of total public property in the County. The factor proximity to public schools received a weight of two based on County official input, schools have guaranteed water connections and the factor proximity to water lines received a weight of three, and many of the schools contained areas with some of the highest temperatures in the County which would score the processed air temperature factor highly with a weight of three. The majority of these public parcels were either within seven miles of the City of Richmond to the north or within five miles of the City of Petersburg to the southeast.

There were 82 privately-owned parcels that contained suitability scores within the 90th percentile if scores (Table 6). All of these parcels were within approximately one mile of public schools. Approximately 86.6% of the parcels were small residential lots, apartments, or offices that were one acre or smaller. The remaining 13.4% of privately-owned parcels were either historic farms, businesses, or properties owned by development companies and were five acres or larger. The majority of these highly suitable parcels were within five miles of either the City of Richmond to the north or the southeast City of Petersburg.

Table 6. *Categories of privately-owned parcels that scored within the 90th percentile of most suitable for urban agriculture.*

Privately-Owned Parcel Category	Number of Parcels That Contained a Highly Suitable Score	Percent of Highly Scoring Parcels
Small residential lots, apartments, or office (≤ 1 acre)	71 parcels	86.6%
Farms, businesses, or other large properties (≥ 5 acres)	11 parcels	13.4%

Case Studies

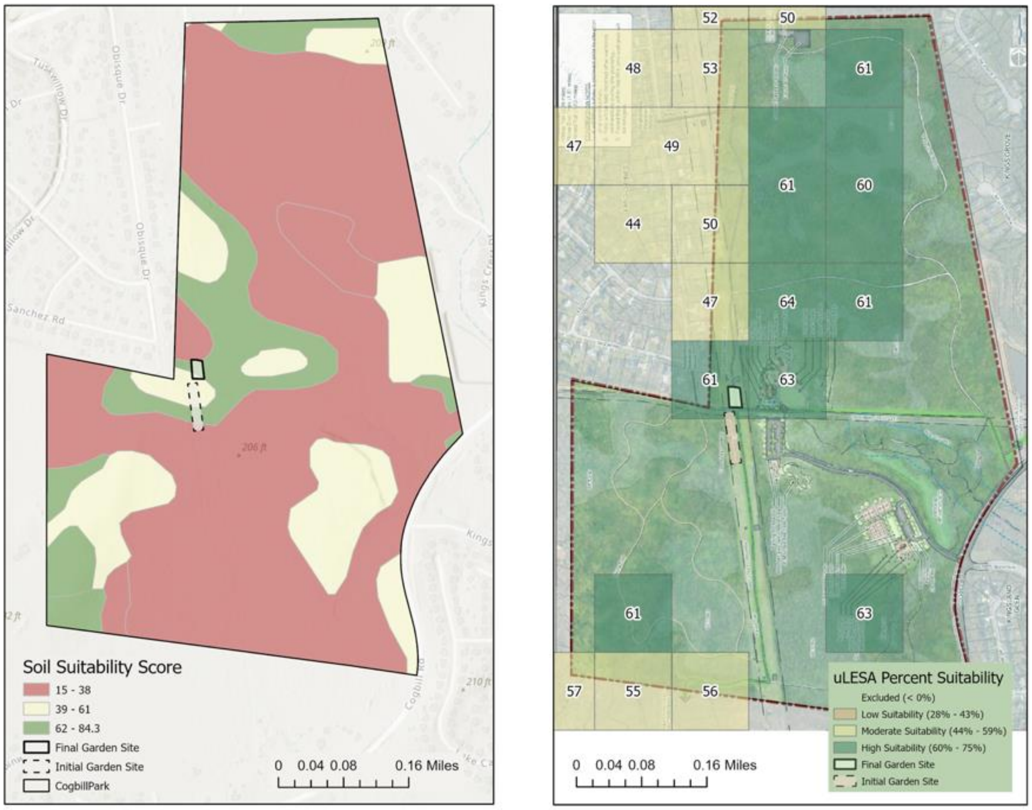
This section presents a deeper investigation into two sites identified as highly suitable by the uLESA model and are of interest to the County and the regional land conservancy: Cogbill Park and Reeds Landing. The following elements are explored in more detail: soil suitability and soil type, ecological importance, percent of the population below the federal poverty line, social vulnerability, and the demographic makeup of residents surrounding the sites. The implications or utilization of each site were mentioned based on the aforementioned factors and how they could benefit the surrounding community.

Cogbill Park

There were a number of public sites of particular interest to County officials. One of these sites included a new County-owned park that, as of early 2023, is in development called Cogbill Park. This park is located in close proximity to residential areas and is approximately 212 acres. The property includes Wetland Mitigation Areas, Resource Protected Areas, and the majority of the property is assigned a C5 general status as an Ecological Core by VDCR's Natural Landscape Assessment. As such, the site serves as an ecological node of forested landscape corridors that create a statewide network of natural lands (VDCR, 2017). The plans for the property include bikeways, trail routes, a new playground, and a community garden. Agriculture would be difficult on the majority of the property, as 135 acres or 64% of the soils on the property are considered aquults, seasonally wet soils where groundwater is close to the surface, usually in winter and spring (NRCS, 2022). Part of the property is bisected by a powerline owned by Dominion Energy, which is protected by a utility easement.

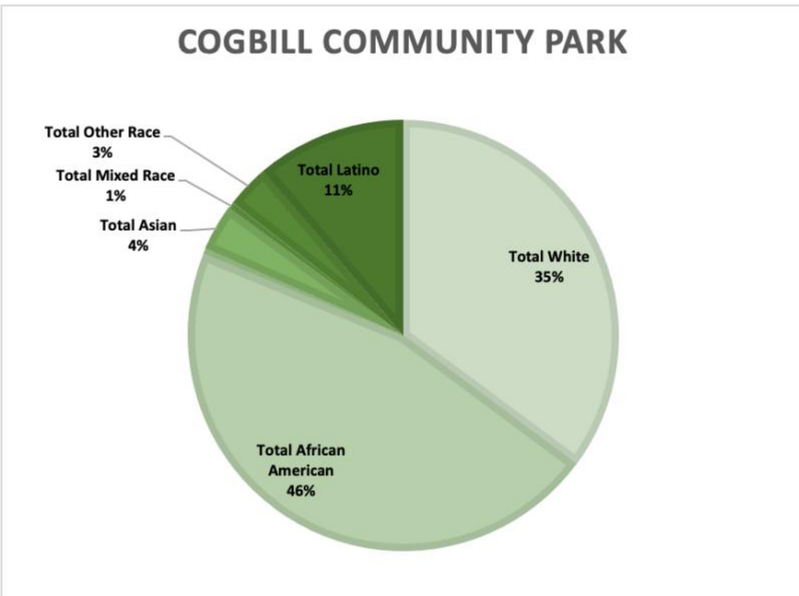
The architect proposed a community garden within that easement. The initial siting of the approximately 0.5-acre garden overlapped with aquult soils (Figure 3). Based on these findings, the County encouraged the architect to move the garden from the aquult soils within an excluded raster cell into a raster cell area that scored 61% suitable for agriculture. The final garden will be approximately 0.2 acres. This highlights one potential use of the uLESA modeling for local governments.

Figure 3. *Cogbill Park soil suitability with the initial and proposed location of a community garden space (left). Cogbill park site plan with uLESA percent suitability scoring with the initial and proposed location of a community garden (right).*



The surrounding area within 1-mile of the proposed Cogbill Park has approximately 27,168 residents (US Census Bureau, 2020). The majority, or 46%, of area residents are African American, 35% of residents are White, and 11% of residents are Latino (Figure 4). The area has a median income of $75,788 and 2,048 individuals are considered below the federal poverty line, or 7.5% of residents (2020). According to the Center for Disease Control's Social Vulnerability Index, the census tract where the park is located is considered highly socially vulnerable with a score of 0.75 out of 1.0 (CDC, 2022). This suggests that the area is highly vulnerable according to 16 factors across four categories including socioeconomic status, household characteristics, racial and ethnic minority status, and housing type and transportation (CDC, 2022). Cogbill Park is also located more than one-mile away from a grocery store, a metric used by the USDA to determine food desert conditions, which may make it difficult for some residents to access healthy foods (USDA, 2023). This garden may provide the opportunity to create a healthy food access point for community members.

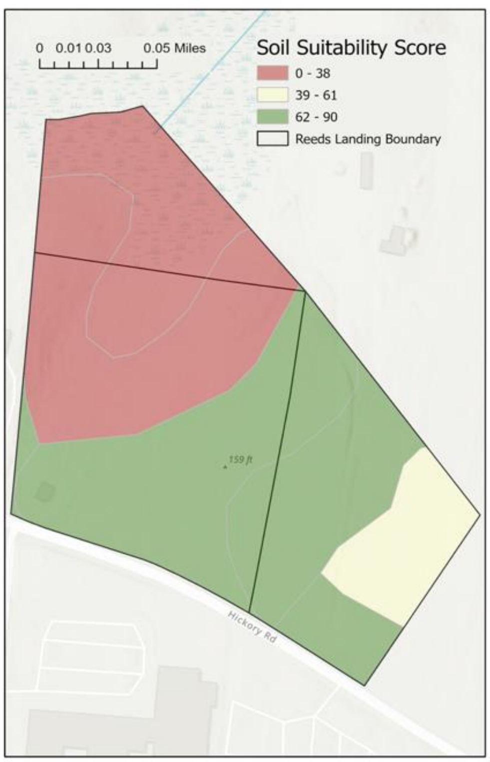
Figure 4. *Chart of the demographic makeup within one mile of Cogbill Park.*

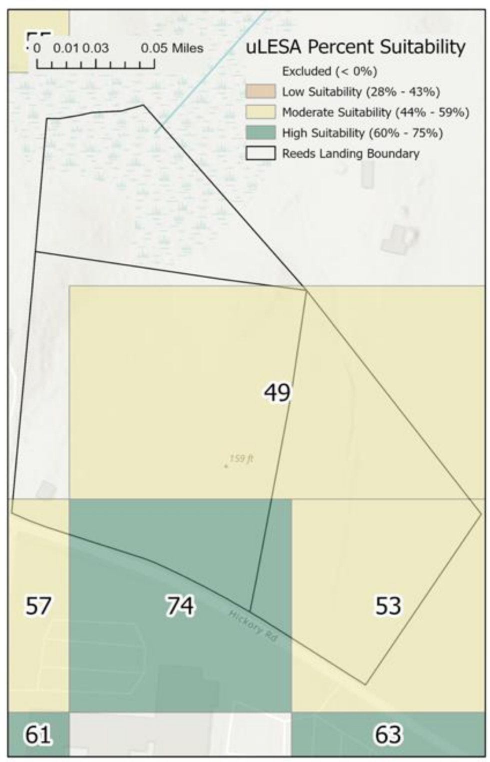


Reeds Landing

A regional land conservancy with the ability to hold conservation and agricultural easements within Chesterfield County was interested in a number of highly suitable, privately owned sites. Reeds Landing is one of those sites. Reeds Landing is composed of two parcels containing approximately 18.5 acres and has been owned by a development company for approximately ten years. This parcel is currently zoned agricultural and there have been multiple attempts to rezone the parcels to residential zoning to build a housing development. The regional land conservancy is interested in the property because it contains prime agricultural land. The property contains 5.2 acres of highly suitable soil for agriculture according to VDCR's Agricultural Model (Figure 5). The second-highest scoring raster cell within the County, with a suitability score of 74%, was located over these prime agricultural soils. The property contains riparian forest surrounding the Big Branch River to the rear of the parcels, which makes up 12.8 acres or 69% of the total area, and is not considered an ecological core according to VDCR's Natural Landscape Assessment. The remaining 5.7 acres is currently fallow land. The uLESA model provided further justification for the regional land conservancy to again seek for a conservation easement to be placed on the property.

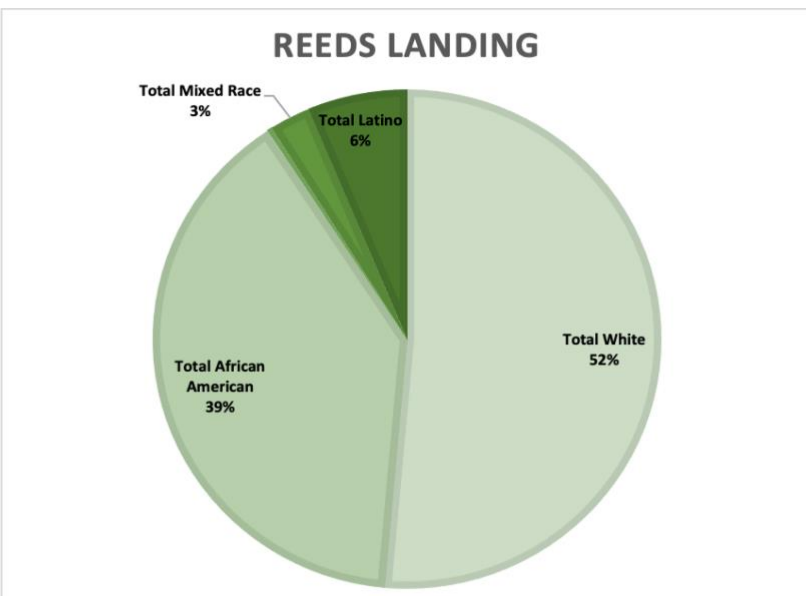
Figure 5. *Reeds Landing soil suitability scoring (left) and uLESA percent suitability scoring (right).*





The surrounding area within 1-mile of Reeds Landing has approximately 7,169 residents (US Census Bureau, 2020). The majority, or 52%, of area residents are White, 39% of residents are African American, and 6% of residents are Latino (Figure 6). The area has a median income of $58,139 and 630 individuals are considered below the federal poverty line, or 8.8% of residents (2020). According to the Center for Disease Control's Social Vulnerability Index, the census tract where Reeds Landing is located has a social vulnerability score of 0.56 out of one (CDC, 2022). This means that the area is moderately vulnerable (2022). The Reeds Landing property is also directly adjacent to Matoaca Middle School. As of 2022, 45.7% of students at Matoaca Middle School are eligible for free or reduced-price school lunches (VDOE-SNP, 2022). This may offer opportunities for a public-private partnership for agricultural education or food production for school lunches.

Figure 6. *Chart of the demographic makeup within one mile of Reeds Landing.*



Study Limitations

There were several limitations to this study that pertain to the uLESA model itself and its broader implications, such as the bureaucratic hurdles for implementation, how the data has the potential for misinterpretation, and the repetitive nature of some factors. The uLESA model's purpose is to locate highly suitable land for urban agriculture and serves as a recommendation that local officials can act upon in their planning decisions. Implementation of these findings could be cumbersome especially if there is political complexity and changes to zoning ordinances are required to ensure agricultural viability. Many counties within the Greater Richmond Region are rapidly expanding and many local government officials prioritize development, as it can increase tax revenues. This may come into conflict with the agricultural conservation goals uLESA model, which may make implementation more complex.

Bureaucratic Hurdles for Implementation

Zoning changes are particularly cumbersome because of the research required and the legal ramifications, which may create a bureaucratic barrier to change as some localities may have limited resources to devote to those endeavors. Zoning considerations include allowing for agricultural infrastructure such as hoop houses, wash stations, and storage buildings that may be essential for season extension, food safety, and every day operations. Another consideration is allowing produce sales onsite to provide another market opportunity for farmers. These complexities require both agricultural and legal knowledge, which many localities do not have within their planning departments. This knowledge barrier makes changing the status quo difficult and may slow the growth of urban and suburban farming because of restrictive zoning policies.

Concurrent with this research, Chesterfield was undergoing Zoning Ordinance Modernization (ZOMod). County officials highlighted urban agricultural usage and framed it more specifically in terms of required conditions for the ZOMod project with the uLESA model results under consideration. The uLESA model also operates under current zoning ordinance in Chesterfield County and officials seek to make residential zoning more compatible with the infrastructure requirements of urban agriculture, such as hoophouses and wash stations.

Potential for Misuse

The uLESA model often scores raster cells located on urban and suburban land higher compared to rural land because the factors favor areas with more infrastructure and closer proximity to County resources. For example, areas within 25 feet of water lines received higher scores than areas outside of that buffer range, which favors places that have connection to County water over rural areas that may not currently have connection. This concept may not be clear and may cause officials to think that rural farmland that did not score highly is not suitable. This may provide justification to develop this area even if it is considered prime agricultural land by other indicators. Further iterations of the uLESA model will need to consider this bias and change the methodology accordingly to ensure that the model could not be used as justification to convert rural prime agricultural land. This methodological change may include running a separate model that includes only the agricultural factors with the addition of parcels that have wells in more rural areas to calculate overall agricultural suitability. Another option includes using population density or the Census Bureau's urban-rural classification (US Census Bureau, 2020). This could be used to create separate models by classification using different factors specific to rural conditions versus urban conditions to decrease incidence of misinterpretation.

The uLESA model is static and built using datasets from 2015-2022. Chesterfield is rapidly developing and the model will need to be updated to keep up with land cover changes and other changes to any of the 20 factors. The next land cover data update for the country will be in 2025. Ideally, the model should be updated then to ensure County officials have the most accurate data. To circumvent some of these issues, the uLESA model could be automated to integrate internal datasets, such as County infrastructure data, and external datasets, such as the NLCD, so that the data is updated frequently to make the model dynamic and accurate for planning decisions.

Repetition of Factors

Due to both the exploratory nature of the uLESA model and the nature of some data sources, the results may be more exclusionary than necessary due to the repetitive nature of some factors or the construction of the methodological categories. For example, the EPA Walkability Index utilizes public transportation stops in its calculations by census tract and there was a separate uLESA factor that prioritized areas within a one-mile distance of bus stops. The proximity to bus stops factor also received a weight of two with the input of County officials. This may overly prioritize these areas when they service a relatively small area of the County, which is mostly located near the border of the City of Richmond and partially down a major thoroughfare, Jefferson Davis Highway. It may be useful to simplify the input factors by using less external modeling and generating more streamlined data internally, such creating “walk time” analyses for walkability instead of using the multivariate EPA model that also includes data related to other uLESA factors.

The model also is potentially more exclusionary than necessary because it contains many more dimensions than just agricultural factors. The equity and heat island effect proxies are important to prioritize areas where equitable resources are lacking or where climate change may impact the surrounding communities the most. It is also important to balance these elements with attempting to identify the most prime agricultural land possible to potentially aid in its conservation. It may be more useful to run two separate models, a model with only the natural and agricultural resource factors and another model with the equity and accessibility factors with the heat island mitigation factor. This will allow for all prime agricultural land located within urban and suburban areas to be identified and the second model will aid in prioritizing which areas should receive these agricultural resources first.

Implications

The uLESA geospatial model is an accessible and repeatable methodology that can be adapted and refined to specific geographical areas. This research created a tool that stakeholders can use to empirically analyze their communities to identify ideal spaces for certain forms of diverse, inground urban and suburban agriculture. The model is localizable, allowing stakeholders to shape analysis factors based on their priorities to define their own community food system. The uLESA model may also help land trusts and conservancies locate prime urban and suburban agricultural land and provide justification for conservation easements.

Local and state level public officials can use the uLESA model to create intentionality in the planning of urban food systems and expand the long-range planning tool kit for local governments. Public planners can use empirical data from the model to guide the placement of agricultural sites into site plans and comprehensive plans. The uLESA model includes a number of factors to mitigate the pitfalls of situating agriculture on ill-suited land, such as avoiding future development areas, ensuring reasonable proximity to water infrastructure, and ensuring soil suitability. This can allow for secure land-tenure for agriculturalists by providing them the best agricultural conditions for success and avoiding areas with high development pressure that may threaten conversion into land uses that may have higher revenue potential. Within Chesterfield County, the uLESA model findings could be integrated into the overall County Comprehensive Plan as well as the Parks and Recreation Comprehensive Master Plan, as many public parks received high percent suitability scores for urban agriculture.

This long-term approach also allows these sites to function as potential green infrastructure. Green infrastructure is inclusive of all open spaces including those screened out of the model for urban farmland. The uLESA model prioritizes situating agriculture within areas with the hottest summer temperatures to conserve permeable cover and vegetation into the future to absorb solar radiation and cool the immediate area. This expands the concept of green infrastructure to include food production spaces, and gives public planners another method for planning for green infrastructure and mitigating heat island effects within the communities that are impacted the most.

Finally, the uLESA model can also be used by land trusts and conservancies, who can leverage the uLESA modeling to improve their targeting of lands for agricultural conservation efforts. Many land trusts are working in rapidly urbanizing regions where protecting high quality agricultural lands against encroaching development is becoming important. Land trust officials could use a uLESA model to seek conservation easements on private lands. In effect, land trust officials can reference an independently created methodology to justify the value of private land for this form of urban and suburban agriculture. When used in this way, uLESA has the potential to grow the capacity of urban agriculture beyond the actions of the public sector.

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