Prioritizing Conservation & Development in Durham, NC

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Executive Summary

Durham, NC is one of the most heavily forested cities in the Southeastern U.S., with more than 50% canopy coverage across the city. Trends in growth and development threaten the city's natural resources; in the last decade, Durham has seen rapid population growth of over 20% alongside increased demand for housing and utilities. Unchecked development leads to a loss of valuable ecosystem services and an increase in urban sprawl, and steps will need to be taken to ensure responsible development over the next few decades.

This Master's Project worked with Trees Durham under Katie Rose Levin (Executive Director) to develop geospatial models to guide Durham County's development. Models incorporate features associated with ecosystem services as well as data associated with development to generate per-pixel scores indicating suitability for development and conservation across Durham County. These scores emphasize the preservation of existing ecosystems while encouraging nodal development around existing corridors, with the goals of reducing urban sprawl. A walkability analysis was also conducted to supplement the models and encourage dense, walkable development. The final products can be used to identify priority areas for development or conservation, both at the county level and at more localized scales.

The first two sections introduce project goals and provide a review of relevant literature that offers insights into analytical choices and model inputs. The third section briefly discusses an exploratory analysis, in which several case study areas of Durham were examined to pioneer the techniques applied at the county level.

Sections four and five detail the generation and application of the cost surface model, which incorporates factors related to development and conservation to generate a development score index across the county. Managed and natural areas, wetlands, and systems with high biodiversity were identified as features most critical to retaining ecosystem services; low scores (indicating poor suitability for development) were applied to areas in proximity to these features to disincentive development. Conversely, density of development, measured by roads, utility lines, and land surface temperature was used to identify areas ideal for nodal development; the model recommends further development take place in these areas, to reduce urban sprawl and promote walkability. Cost surface products were also applied to undeveloped parcels in Durham County to associate results with a common administrative unit. Additional analyses were conducted at this stage to generate priority layers that identified parcels at risk of development, as well as those containing steep slopes in proximity to floodplains.

Sections six and seven assess the socially and economically vulnerable Durham neighborhood of Braggtown as a case study. A walkability analysis examines the district's permeability to foot traffic and calculates least-cost paths between features such as schools, commercial areas, and high-density residential blocks. Further comparative analysis examines of all products (cost surface, parcel products, priority overlays, and walkability analysis) in the context of the Braggtown neighborhood.

Durham is a rapidly developing but still relatively nascent urban area and has the opportunity to expand in ways that retain its canopy coverage and beneficial ecosystem services while creating human environments that are livable, walkable, and conducive to human health and well-being. This report makes several recommendations concerning the use of its geospatial models to achieve these goals:

- The cost surface products generated by these models offer a large-scale method to guide development and determine focal areas, but should be used with caution at local scales, as they are limited by their spatial resolution. Cost surface inputs should be updated frequently (every 2-3 years at minimum) to ensure accuracy and reliability.
- Parcel products are a better solution for examining results at local scales (e.g., neighborhoods), and offer the most utility for selecting individual targets for conservation or development. Parcels should be researched and investigated on-site to confirm accuracy and establish specific context not included in the model. Managed area, priority area, and flood risk overlays offer additional comparative power when applied alongside parcel-level products. Parcel data, managed area data, and priority areas should be updated yearly to reflect changes in zoning and ownership.
- Walkability analyses are most effective at smaller scales (e.g., Braggtown), and are best applied with specific sources and destinations in mind. Generation of a least cost path is the most direct way to designate focal areas related to walkability. Analyses should be sure to include areas adjacent to the study area to accurately reflect real-world patterns of movement.
- An improved methodology for tracking current development and predicting future development would help these models better prioritize areas for conservation.
- A full-scale analysis of the relationship between development, gentrification, and poverty would provide additional relevance to these models, especially in the context of Durham's growing population and changing demographics.

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I. Introduction

Many cities across the Southeast are experiencing rapid growth. One of the fastest growing areas in the region is the Triangle in North Carolina, which includes Raleigh, Durham, and Chapel Hill. Durham in particular has experienced a nearly 20% increase in population over the last decade (World Population Review, 2020), accompanied by commensurate development. While Durham remains one of the most densely forested cities in the southeast, with an estimated 52% canopy coverage in 2015 (Hancock, Vanko, & Xiong, 2020), that proportion is subject to decline as an increasing population leads to demand for new housing, facilities, and commercial areas. Recent trends in land cover suggest that this process has been in effect over several decades; according to National Land Cover Database (NLCD) data, Durham's impervious surfaces increased by 13% from 2001 - 2016.

Although development pressures are significant, the city has recognized the importance of urban canopy, and the Urban Forestry Division's management plan calls for 55% canopy coverage by 2040 (City of Durham, 2018). In order to achieve this ambitious goal, the city has partnered with other organizations, such as our client, Trees Durham, to plan and execute strategies to meet coverage targets. The mission of Trees Durham is to combat climate change by creating a healthy, sustainable, and socially just tree canopy across Durham. They achieve this mission through research sponsorship, education, tree planting and care, as well as through forest and environmental justice advocacy (Trees Durham, N.D.).

Trees Durham has used and worked with several other Masters Projects in the past. Cooper, Liberti, and Asch (2016) surveyed Durham's urban canopy and established a decision analysis framework for tree planting based upon a variety of environmental and socioeconomic factors, including canopy coverage, stormwater benefit, and historic redline data. Hancock, Vanko, and Xiong (2020) created a geospatial model based on community surveys to determine priority tree planting areas and modeled future changes in Durham's canopy under different development scenarios.

This master's project seeks to build upon the work of previous projects. While past work has focused on street trees and urban canopy specifically, this project more broadly seeks to examine Durham's development frontier: to qualify key environmental services in as-of-yet undeveloped areas, to gauge where development would have the greatest impact on existing services, and to determine sites best suited to development with a focus on increasing density for a more livable and walkable urban environment.

- Section 2 offers a brief literature review describing the inputs into our models and the reasoning (and evidence) behind our choices.
- Section 3 details the exploratory portion of our analysis, which provided the foundation for our more comprehensive county-wide examinations of factors.
- Section 4 discusses the creation and use of our primary cost surfaces (on development suitability), both for the county and the sector level. This section also contains a detailed overview of the data layers and the weighting process.

- Section 5 discusses the parcel-level analysis of development priorities, as well as additional overlays that incorporate ancillary factors such as flood risk. This section also includes a comparative analysis whereby parcel products are compared to existing trends in conservation and development.
- Section 6 covers a case study of the walkability of Braggtown, a historically black Durham neighborhood, examining high-density residential areas proximity and access to other community locations. This serves as a potential extrapolation of our projections in a small-area planning space.
- Section 7 offers our conclusions and recommendations for Trees Durham, the city, and future collaborators.

II. Literature Review

Air Pollution

Urban greenspaces have powerful reductive effects on concentrations of gaseous and particulate air pollutants common to cities such as SO_2, NO_2, Ozone, and PM 2.5. Trees absorb gaseous particles through respiration processes and physically trap larger particulate matter. Nowak et al. (2006) estimated removal of 711,000 tons of pollution per year by urban trees in the U.S. Urban greenspaces also provide a buffer between emissive sources and human activity, diluting the concentrations of harmful chemicals before humans are exposed (Hewitt, 2019; Klingberg et al., 2017). Strategic placement of greenways and retention of existing natural barriers can help reduce the negative health effects of emissions on human populations.

Hancock, Vanko, & Xiong (2020) modeled Durham's air quality using EPA-provided PM10 concentrations as a proxy for overall air pollution. They also used distance from major roads (up to 150 ft.) as a proxy for pollution based on existing literature. This study suggests maintaining urban air quality in Durham by encouraging the retention of greenspaces, especially those close to existing roadways.

Heat Mitigation

Urban heat poses one of the most serious threats to human and environmental health within cities. Changes in land cover related to urbanization, including decreases in vegetation and increases in impervious surfaces with low reflective capacity such as parking lots are correlated with significant increases in mean land surface temperature (Fonseka et al., 2019; Weng & Fu, 2014). Increased temperatures can affect a wide variety of factors, such as human cardiovascular health, the prevalence of disease vectors, biotic processes such as senescence, and abiotic processes such as precipitation. While urban heat islands are a consistent phenomenon, with cities almost always being warmer than surrounding rural areas, studies have shown that urban greenspaces and trees have an ameliorating effect on urban heat through absorption of solar energy, evapotranspiration, and shading (Markevych et al., 2017).

A previous MP used Landsat thermal data to establish zones of high and low relative temperature within Durham; areas of high temperature were correlated significantly with impervious surfaces, while there was a statistically significant relationship between tree cover and negative temperature effects (Hancock, Vanko, and Xiong, 2020). This study hopes to account for urban heat reduction through similar methodology and prioritize greenspace for conservation to maximize heat reduction.

Social Inequality in Urban Environments

The positive effects of ecosystems, and by extension the negative effects that they ameliorate, are not evenly distributed throughout cities. Research has shown that lower-income, predominantly minority neighborhoods have fewer greenspaces and lower canopy coverage than their wealthier counterparts, and that residents in these neighborhoods suffer increased impacts from health problems associated with urban environments, such as respiratory disease and heat-related illness (Hoffman, 2020; Wilson, 2020). In many cases, modern urban inequality can be attributed to long-term development practices: throughout the U.S., a policy of "redlining", whereby certain neighborhoods were designated as high risk for home loans, has had lasting effects on modern urban structure. Hoffman (2020) conducted an aggregate study of 239 U.S. cities with existing redlining maps and found heavily redlined zones (designated as risk-level "D") were on average 2.6 ^{o}C warmer than the low-risk zones (designation "A"). Two previous MPs examined Durham's legacy of redlining and found that risk level "D" zones displayed almost 20% less tree cover than the city's overall average of 52% (Cooper, Liberti, & Asch, 2016; Hancock, Vanko, & Xiong, 2020).

While the localized scale of this project precludes the use of redlining maps (they only occur in previously developed areas), we attempt a similar examination of inequality in modern greenspace using demographic data to designate priority areas for greenspace preservation and creation. As some of these areas occur within the projected sphere of development, they present an opportunity to help rectify some of the systemic inequalities present in past development strategies.

Urban Densification and Walkability

In contrast to the drivable suburban development pattern that has been promoted across the U.S. over the last century, cities are now moving toward more dense development (Sisson, 2019). Urban densification allows cities to tap their full potential, decreasing energy consumption and infrastructure costs and improving land use efficiency (Mittra, 2019). To further enhance the benefits of densification, development needs to focus on mixed use: having a variety of goods and services located within a walkable distance from residential accommodations encourages more sustainable modes of transportation such as biking and public transport, while bringing a larger consumer base to local businesses. Densification and mixed-use development reduce the need for private transportation, lowering carbon emissions and improving air quality for human health (Caine, 2017).

Corridor Connectivity

Green space in urban areas is often heavily fragmented, surrounded by features such as roads and buildings that are inimical to wildlife. Fragmentation greatly hinders the migration of species from one habitat to another, often leading to a loss in biodiversity (Gleason, N.D.). Moreover, movement between habitat patches through manmade features can lead to increased human-wildlife conflict in urban and suburban environments (such as deer attempting to cross a road, which puts both humans and wildlife at risk). Corridors help ease travel between habitat patches, protecting local biodiversity and ecosystem services and decreasing conflict between humans and wildlife (Austin, 2012). Corridors can also be used to improve human mobility through the landscape, connecting people to green spaces and acting as safe mobility networks linking residential areas to areas of mixed land use (commercial and/or recreational) (Sisson, 2019).

The Cary greenway is an example of one of the most successful greenway projects in the United States. Cary's strategy was to preserve linear parcels of land along local floodplains and wooded stream corridors, providing public access to these areas. The resultant trail network extends over 80 miles and connects neighborhoods to one another, as well as with parks and popular shopping destinations (Town of Cary, N.D.). The use of auxiliary features such as utility lines have also been used to form greenways. Transmission lines often stretch alongside residential and commercial areas, and vegetation below them is typically cleared for maintenance and safety purposes. Municipalities such as in Houston, Texas have taken advantage of these already-cleared areas and have turned them into bike paths to improve mobility around the city. This practice also saves money by reducing the area around the transmission lines that must be frequently mowed (Burns & McDonnell, 2017).

Ecosystem Services

As urbanized areas expand across the United States, cities continue to be decoupled from nature. However, everyone who lives in these cities depends upon the natural environment and ecosystem services (URBES project, 2013). Ecosystem services are defined as "the outputs, conditions, or processes of natural systems that directly or indirectly benefit humans or enhance social welfare" (Johnston, 2016). These services include food, water provision and filtration, security, health benefits, and protection or buffering from harmful impacts of disasters and climate change. Unfortunately, while preserving or incorporating ecosystem services within cities can markedly improve people's quality of life, they are often not considered during the city planning process (The URBES project, 2013). Conserving land that provides valuable ecosystems services to humans also protects biodiversity. The relationship between natural species biodiversity and ecosystem services is complex and often synergistic, with loss of even a single species having the potential to disrupt system processes and reduce the benefits provided (Zari, 2018).

Cities have often recognized the importance of ecosystem services too late, leading to significant investment into in the reestablishment of previously removed green spaces. For example, cities have engaged in the restoration or complete rebuilding of wetlands for flood reduction, waste filtration, and replenishment of drinking water (National Resource Council, 1992). In these scenarios, municipalities spend significantly more money for restoration efforts than if the ecosystem services had been protected in the first place (The Dollars and Sense of Wetland Preservation, 2021); cities will save more money if the areas of high conservation value are accounted for in the planning phase and appropriately preserved.

Durham still retains many of its ecosystem features and has an opportunity to develop with preservation in mind. On a county-wide scale, this project incorporates areas of high ecological value into a cost surface for use in sustainable development planning, aiming to encourage the preservation of areas of high biodiversity and vital ecosystem services.

Wetlands & Flood Zones

One of the most pressing issues caused by rapid urbanization is the disappearance of wetlands. These ecosystems are not only necessary to maintain biodiversity for conservation purposes; they also provide services to cities, such as stormwater retention. Removal of wetlands leads to increased stormwater runoff, which can cause flooding and worsen the quality of the groundwater in a watershed (Malaviya and Singh, 2012).

An underappreciated part of urban ecosystems is constructed wetlands, which are often considered not as effective as 'natural' wetlands. According to Holtmann et al. (2017), artificial bodies of water can support wildlife in a similar capacity to natural ponds. Constructed bodies of water can also remediate contaminants to a similar degree as natural ecosystems if created with that purpose (Scheffers and Paszkowski, 2013). However, even when wetlands are constructed or are designated for conservation, their quality is typically reduced. Patenuade et al. (2015) concluded that cities need to work on wetland restoration while also creating an effective buffer against impervious surfaces.

Flooding is becoming an increasing risk as climate change leads to more frequent and extreme precipitation events while continual development reduces urban areas' ability to expel water through porous surfaces. Floods can lead to property damage, public safety risk, and disruptions in people's lives and the local economy. In North Carolina, flooding in proximity to confined animal feeding operations (CAFOs) can lead to waste and pollutant run-off that disproportionately affects African American communities (Wing et al., 2002). Currently, the risk of developing flood-prone areas is estimated by the Federal Emergency Management Agency (FEMA) with its National Flood Insurance Program (NFIP), which assigns risk through flood mapping (Wang et al. 2017). However, FEMA regulations and research are sparse regarding the relationship between slope and proximity to areas deemed high flood risk. This project seeks to account for areas adjacent to floodplains and discourage development of steep, flood-prone slopes.

III. Site Selection / Exploratory Analysis

Although this project's end results focus on capturing trends at the county level, the initial aims were to model development and quantify ecosystem services at much smaller scales, with a focus on examination of specific sites as case studies for the cost surface model. This section describes our exploratory analysis.

To identify individual residential parcels that could serve as case studies for several possible development scenarios, county-wide residential parcel data were obtained from Durham Open Data (City & County of Durham, 2020). The parcel layer was restricted to show only parcels that met chosen criteria. To ensure that the land area of individual parcels would be large enough to make meaningful recommendations for future development, only parcels greater than 5 acres were selected. In addition, selections were limited to parcels that had 15% or less of impervious land cover to eliminate already-developed areas. These restrictions resulted in a layer of parcels that met the basic requirements for potential site selection.

Each parcel was then manually examined to determine if it had any of several features of interest, such as dense forest, proximity to wetlands, or proximity to dense corridors of development. To aid in selection, parcel data were displayed over current base map imagery in ArcGIS Pro to identify what was around and in each parcel. Two additional data layers were used to assist in site selection. The first was a shapefile obtained from NatureServe (NCNHP, 2020b) displaying natural areas within Durham. This layer was used to identify parcels located on or near areas of high ecological importance. The second was a data layer on household income; parcels with low to medium household income were deemed higher priority. Previous MP work, as well as the client's specific knowledge of Durham, suggests that these areas receive fewer benefits of urban greenspaces compared to wealthier areas.

Undeveloped parcels were considered ideal candidates if they were near existing infrastructure, near areas of ecological significance (wetlands, lakes, forests), or near development. Using these criteria, 28 parcels were selected for consideration.

Upon further review, several areas within Durham County had clusters of ideal parcels. To increase the scope of the analysis and examine connective zones between these parcels, square sectors were created around three separate clusters. These clusters were chosen in three different locations across the county: Braggtown, Lowe's Grove, and East Durham. These particular locations were selected because they captured a variety of income levels, represented different degrees of urban density, each contained several optimal parcels, and each contained areas of high ecological importance. Each sector was drawn around the cluster of parcels in a way that captured nearby commercial or biological areas that could influence development. These sectors defined the areas that were initially examined in our cost surface analysis.

IV. Cost Surface Development

Introduction

After consultation with Trees Durham, the sectors defined during the exploratory analysis were affirmed as suitable study areas. However, an additional examination of the same factors at the county level was requested by the client. Data products were therefore developed at both the sector level and the county level.

Cost surfaces were developed for each area of interest to represent suitability for development. Cost surfaces are commonly used for processes such as least-cost pathing, wherein a pixel's value represents the cost of traversal, and a path is generated by sequentially selecting pixels of least value.

This methodology was not concerned with pathing, but rather the "cost" of developing a pixel based on proximity to existing features and loss or disruption of others.

The cost surfaces integrated a number of factors relevant to both development and conservation; we aimed to generate a surface that would encourage nodal development by assigning higher values to pixels already adjacent to existing development, and lower values to highly undeveloped areas or areas with priority conservation features. The methods section describes the process behind the cost surface generation, including integration of various layers, development of key datasets, and reclassification and weighting schemes that led to the final product. The results section presents maps of the various products, as well as metrics that summarize the extent of each surface.

Materials & Methods

Cost surfaces were generated at two separate scales to fulfill the needs of the client. The county-level analysis included more available inputs and factors, but produced a more generalized result, while sector-level analyses were more specific to each subsector, including only factors contained within the area of interest.

Acquired Data Sources

Data were obtained from a number of sources to represent biotic, abiotic, and human influences across the study area. Data were chosen based on relevance to chosen criteria, then analyzed for suitability. Some data required additional manipulation before integration into the cost surface.

<u>Median Household Income</u>

Median household income data at the census tract level were included to account for issues surrounding poverty and gentrification. Durham has a history of disenfranchisement of minority and low-income homeowners, from racist redlining policies in the 1930s that discouraged investment in predominantly black neighborhoods to urban renewal policies in the 50s and 60s that displaced and fragmented black communities (De Marco & Hunt, 2018). In recent decades, population trends and changing national attitudes on urban living have resulted in rapidly rising housing prices, especially in historically impoverished areas adjacent to the city core.

In order to discourage aggressive development of such neighborhoods, the model rates census tracts with the lowest household income with lower development scores. Although this helps adjust for the propensity for development in Durham's poorest communities, gentrification and stratified development are hugely complex issues that would certainly benefit from a full, standalone geospatial analysis.

As the most recent census data at the time of analysis were from 2010, Data from the 2015-2019 American Community Survey provided the most up to date metrics on household income at the census tract level. Data were obtained through ESRI's data repository (U.S. Census Bureau, 2020).

The U.S. Department of Health & Human Services' 2020 poverty guidelines for a family of four were referenced for determination of the poverty line, used in reclassification thresholds (Button, 2020).

Roads Data

Road data were obtained through Durham Open Data and were current as of September 4th, 2019. Several data layers were obtained through Durham Open Data, the county's open data repository. Durham's Open Data site is jointly maintained by the city's Technology Solutions department and the county's Information Services & Technology department and offers a wide variety of publicly available government-held data (City & County of Durham, 2020).

Roads were integrated into the model to capture the extent of current development; areas enmeshed in a high-density road network were deemed more appropriate for nodal development than, for example, parcels surrounded by undeveloped land or forest. Road data were obtained as vector data in the shapefile format and reprojected into NAD State Plane NC FIPS 3200 for integration with other shapefiles and spatial rasters.

Transmission Lines

Transmission line data were not available at the city or county level, but were instead available nationally, accessed via the Homeland Infrastructure Foundation-Level Data repository (HSIP Team, 2020). Data were up to date as of July 23rd, 2020.

These data were included to capture the spatial footprint of transmission line corridors as they relate to conservation, development, and walkability. Transmission lines typically require a buffer zone of anywhere from 70 to 180 feet (or roughly 20-50 meters) depending on voltage. Land use within buffer zones is highly restricted by easement agreements between landowners and energy companies (Duke Energy, 2020). Such restrictions make transmission lines potential zones for habitat connectivity or walking trails.

Data were obtained in shapefile format (line-vector) and reprojected into NAD State Plane NC FIPS 3200 for integration into the GIS.

Water & Sewer Lines

During the initial planning phase, water and sewer utility lines were going to be incorporated into small area planning at the sector level to guide development of new lines, taking factors such as walkability, slope, wetlands, and existing infrastructure into account.

However, when the primary products shifted to cost surfaces highlighting parcels for conservation and development, water and sewer utility lines became inputs for the cost surface. Utility lines were input into the model to encourage development close to pre-existing utilities and minimize environmental harm caused by the construction of new lines.

Data were obtained from the Durham County website as line vector shapefiles (Durham County NC, 2020)

Conservation Inputs - Managed, Natural, and Biodiversity Data

Conservation data were obtained through the North Carolina Natural Heritage Program's website (NCNHP, 2020a, 2020b, 2020c). The two shapefiles used were the Natural Heritage Natural Areas

(NHNA) and the Managed Areas (MAREA), both of which were last updated in July of 2020. An additional dataset assessing priority areas for the conservation of North Carolina's biodiversity and wildlife habitat was also obtained (Last updated April of 2020). These data sources were chosen because they provided heavily evaluated data on conservation areas, land important to ecosystem processes, biodiversity, and habitat connectivity. These data were also easily accessible and up to date.

The NHNA shapefile identifies both terrestrial and aquatic sites that the Natural Heritage Program found to have significant conservation value, based on the presence of intact natural communities or important animal assemblages. The MAREA shapefile identifies fee-simple properties as well as easements that have recognized natural resource conservation as one of their management goals.

Initially these layers were used to help guide the site selection process, to ensure that at least some of our parcels were located adjacent to or within areas of ecological importance. The project later changed scope and focused on creating a series of cost surfaces to guide future development. Here these layers were used as a proxy to identify land that contained valuable ecosystem services. The layers were then assigned a relatively high weight so that they would show up as high priority areas for conservation in the resulting cost surface.

Processed Data Sources

While most of the inputs for the cost surface layers were obtained from existing datasets, certain key inputs were unavailable or deemed less than adequate for integration into the cost surface. Extra steps were taken to generate data layers to fulfill the needs of the study.

Two primary inputs were derived in this fashion. A new wetlands raster layer was developed from satellite imagery to replace the dated National Wetlands Inventory dataset, and a land surface temperature (LST) raster was created to capture up-to-date thermal information for the county.

Wetlands Layer

Wetlands contribute extensively to ecological services through functions such as stormwater retention and nutrient absorption, and wetlands in urban landscapes demonstrate marked benefits for public and environmental health (Cimon-Morin & Poulin, 2018). Furthermore, wetlands are frequently priority conservation targets in the eyes of stakeholders. For these reasons, wetlands were deemed an essential element in our cost surface.

Rather than analyzing the individual value of each wetland (a process beyond the scope of this analysis), wetlands were categorized based on type. Lakes, ponds, riverine systems, and wetland forests were all evaluated as high priority conservation targets, while wetland forests were valued as mid-to-high priority. This analysis included artificial ponds as well, which not only service to retain stormwater but can also provide habitat services (Holtmann et al., 2017). From a conservation perspective, each wetland and body of water was integrated into the model regardless of factors such as size, vegetation, or artificiality.

Existing wetland data were deemed inconsistent. A classification analysis was carried out in order to supplement existing wetlands data and thereby enhance the accuracy of cost surface models.

Data

The initial source of wetland data was the National Wetlands Inventory (NWI), which is derived from high altitude imagery and supported by the U.S. Fish and Wildlife Service (FWS). Geospatial data describing wetlands were downloaded from the NWI's Wetlands Mapper site in the form of shapefiles for the entire state of North Carolina (U.S. Fish and Wildlife Service, 2020) While the NWI dataset was accessible, highly descriptive, and covered the entire study area, it was out of date at the time of this study, and many of the smaller polygon features were inaccurate. This inaccuracy required further analysis to attempt to correct.

Landsat 8 imagery was obtained in order to generate an updated classification of wetlands in Durham County. While more accurate or high-resolution remote sensing datasets were available, Landsat images were selected for their accessibility and compatibility with other raster data, and because we wanted to make this process replicable as possible for other municipalities or organizations with limited financial resources.

Data were filtered and acquired through the USGS Earth Explorer site (USGS, 2020). An image from October 2020 was chosen for its minimal cloud coverage and imported into ENVI for atmospheric correction and further manipulation (Harris Geospatial, 2017)

Process

In ENVI, the Landsat 8 image was run through four different indices to emphasize bodies of water in Durham County. Normalized Difference Vegetation Index, the Tasseled Cap transformation, the Normalized Difference Water Index, and the Modified Normalized Difference Water Index were all applied. These four were chosen because of their prevalence, both in geospatial analysis software and in the literature (Carle, 2011; Han & Nui, 2020; McFeeters, 1996; Xu, 2006). Equations for the three indices are presented below. After examining the results of each index, the Tasseled Cap transformation was chosen as the best candidate for classification.

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{2}$$

The Tasseled Cap image was run through two different classifications, supervised and unsupervised. Several iterations with differing numbers of classes were performed to determine which worked best to separate bodies of water from all other land cover types. The result chosen was an unsupervised classification with 20 iterations and 10 classes, as it had the least error. Classes were then merged into two categories, Riverine and Lake/Pond, with the categories representing other land covers being deleted, as this analysis was only meant to identify bodies of water. Majority/minority and sieving tools were applied to remove single pixels. The file was then moved to ArcGIS Pro and merged with the existing NWI shapefile for integration into the cost surface model.

Land Surface Temperature

Land Surface Temperature (LST) data were included in the analysis to quantify the thermal effects of impervious surface on Durham County. Hancock, Vanko, & Xiong (2020) utilized thermal data to prioritize tree plantings in Durham's most heat-prone areas. This analysis applied similar methodology, converting remote sensing imagery to land surface temperature using proven methodology (Fonseka et al., 2019; Sobrino et al., 2004; Weng et al., 2004).

Data

Land Surface Temperature data were derived from Landsat-8 imagery. Landsat 8's TIRS (Thermal Infrared Sensor) captures at-sensor temperature brightness at a spatial resolution of 100 meters resampled to 30 meters (NASA, 2013). This resolution was consistent with other datasets we used, such as our wetland layer, and provided adequate spatial resolution for the scale of the study. Only band 10 from the TIRS was utilized, as Landsat 8's band 11 has been shown to exhibit significant errors (Cristobal et al., 2018).

Google Earth Engine (Gorelick et al., 2017) was used to select, pre-process, and download Landsat imagery. Images were selected from the Tier 1 Top of Atmosphere (TOA) collection; LST calculations are typically performed on at-sensor brightness temperature values, which are already radiometrically calibrated in tier-1 collections (Chander et al., 2009).

Code was developed to screen images from Summer 2020 (between June 1 and September 1) to capture seasonally high heat levels, and to limit the images to the study area (Durham County). Three available images from the chosen date range were then filtered by metadata to include only images with less than 10% cloud coverage. The least cloudy image was selected (corresponding to 07/20/2020) in order to minimize the effects of cloud cover. The final image was exported as a GeoTIFF for further manipulation in ArcGIS Pro.

In order to perform calculations of LST, NDVI (Normalized Difference Vegetation Index) for the chosen date was also required for estimations of emissivity. Google Earth Engine was utilized to obtain Landsat-8 tier-1 surface-reflectance (SR) images from the same date. Surface reflectance images are atmospherically corrected to remove the various scattering effects of atmosphere on EM wavelengths and are therefore more suitable for determination of NDVI values. Code was utilized to calculate and add an NDVI band to the image. A cloud mask was also applied at this stage using Landsat 8's QA bands and carried over for all subsequent portions of the analysis. Products were exported as GeoTIFFs for integration into the ArcGIS model.

Calculation of LST

LST calculations were performed in ArcGIS Pro. While multiple approaches exist for converting at-sensor brightness temperature to LST, many require site-specific input data, such as in-situ measurements of water vapor and air temperature (Fonseka et al., 2019). To adhere to time constraints and logistical limitations, this study utilized a formulaic approach developed by Weng et al. (2004) that does not require additional inputs.

Land Surface Temperature was derived from at-sensor temperature brightness using the following formula:

$$S_t = \frac{T_B}{1 + (\lambda \times T_B/\rho)\ln\varepsilon} \qquad (3)$$

Where λ is equivalent to the wavelength of emitted radiance (an average of 10.8 for Landsat-8 band 10), T(B) is at-sensor brightness temperature, and ρ is a constant derived from Plank's constant divided by the speed of light over Boltzmann's constant, equal to $1.438 * 10^{-2}$ meters Kelvin.

ε represents the emissivity of the underlying terrain, which can be broadly determined through use of NDVI thresholds.

Determination of Emissivity

Several methods exist to determine emissivity based on remote sensing data. This project uses NDVI thresholds to assign emissivity values to a raster image, based on Fonseka et al. (2019) and Sobrino et al. (2004). Emissivity values are assigned based on NDVI thresholds as shown in Table 1.

Table 1. NDVI Thresholds for Emissivity Values

NDVI Range	*Emissivity Value (Est. Terrain Type)*
< 0.2	.973 (bare soil)
0.2 to 0.5	Determined by equation (4)
> 0.5	.99 (vegetation)

For values NDVI values between 0.2 and 0.5, an additional equation (4) was applied to determine emissivity following Sobrino et al. (2004)

$$\varepsilon_{TM6} = 0.004\ P_v + 0.986. \qquad (4)$$

Where P(v) is the proportion of vegetation, determined by equation 5:

$$P_v = \left[\frac{\mathrm{NDVI} - \mathrm{NDVI}_{min}}{\mathrm{NDVI}_{max} - \mathrm{NDVI}_{min}}\right]^2 \qquad (5)$$

P(v) values were derived from the Landsat-8 surface reflectance NDVI values and utilized in equation 2 to generate emissivity values for pixels between 0.2 and 0.5 in value. A final emissivity raster was generated by combining from the resultant values with static values shown in Table 1.

For the Durham County area, further manipulations were necessary to account for large water features such as Falls Lake, which exhibited incorrect NDVI values because of cloud reflections. Steps were taken to apply uniform emissivity values to prevent errors in the final LST raster.

The existing wetlands layer was used to create a polygon feature class of lake features. This feature class was converted to a raster layer and used to uniformly set NDVI values within the raster layer to a highly negative value. Next, the emissivity value of water was set to .9926 based on known values for Landsat-8 band 10 (Vanhellemont, 2020) and applied to the thresholding process to produce a reasonable emissivity value wherever water was present in the NDVI raster.

The final thermal layer provided a continuous surface across Durham County (excluding areas masked for clouds) that illustrates Durham's heat island effects.

Cost Surface Development

After data acquisition and preprocessing, all data products were imported into ArcGIS Pro for cleanup, preparation, processing, and integration into the cost surface model.

To fit all of the data to the same spatial orientation, vector datasets were clipped to the Durham County Boundary. Raster datasets were similarly clipped using the Extract by Mask tool. Environmental settings were applied to mask all resultant products to the County Boundary and to establish the data projection as NAD State Plane NC FIPS 3200.

Euclidean Distancing

To establish the spatial effect of line and polygon features (such as roads or sewer lines) across the entire study area, Euclidean distance rasters were applied to features to generate a series of continuous raster surfaces across the study area. Euclidean distances were calculated using geodesic distancing; models are included in the appendix.

Euclidean Distancing was not applied to all features; raster features that were already continuous across the study area (LST, biodiversity) or those that represented discrete features (wetlands, census tracts) were exempted.

Reclassification

The Reclassify tool was used to standardize the scalar effects of all input factors into the final cost surface. For the local sector cost surfaces, a 0-10 scale was applied, with 0 representing areas completely unviable for development, and 10 representing areas best suited to development. This scale was chosen after testing several different schemes to produce a comprehensible range of final values (within the 1-100 range). At the county level, the range of values was scaled up to match the increase in map scale (1:20,000 to 1:150,000), producing a 0-75 scale.

Most distance rasters were reclassified linearly, but several were adjusted to represent specific distance effects we wanted to capture:

The distance to wetland layer included a 40-meter buffer set to 0 to discourage development within a mediated stream buffer distance.

Trails were buffered at 10 meters with a value of 0 to account for safe walkability, and to encourage preservation of a vegetative buffer.

Roads were buffered similarly. Values at 10 meters were set to 0 to discourage roadside development and encourage the retention of vegetative buffers, which have been shown to reduce the dispersal of exhaust particles to adjacent areas and improve air quality for pedestrians (Hewitt et al., 2020; Klingberg et al., 2017).

Transmission Lines were buffered at 100 meters with a value of 0 to account for the utility-mandated buffer zone (in which development is prohibited).

Non-distance rasters were also reclassified; specifics related to individual layers can be found in Table 2. For all rasters, no-data pixels (such as cloud-masked pixels in the LST raster) were set to the median value of the scale to minimize their impacts in the final product.

Table 2. Relative Scaling of Each Input into the Cost Surface, Including any Specific Buffering

Feature	Scale at 1:20,000	Scale at 1:150,000	Notes / Special
Distance Rasters	*(Close to Far Values)*		
Distance to Managed Area	1 to 10	1 to 75	
Distance to Natural Area	1 to 10	1 to 75	
Distance to Wetland	0 to 10	0 to 75	*40m Buffer @ 0*
Distance to Trail	10 to 1	75 to 0	*10m Buffer @ 0*
Distance to Road	10 to 1	75 to 0	*10m Buffer @ 0*
Distance to Transmission line	10 to 1	75 to 0	*100m Buffer @ 0*
Distance to Water Line	10 to 1	75 to 1	
Distance to Sewer Line	10 to 1	75 to 1	
Discrete Rasters	*(Low to High Values)*		
Biodiversity	10 to 1	75 to 0	
Wetlands	*Variable: 0 for Riverine, Lake; 4 for Freshwater Forested or Shrub Wetland*	*Variable: 0 for Riverine, Lake; 15 for Emergent Wetland, 30 for Freshwater Forested or Shrub Wetland*	
Median HHINC	0 to 10	0 to 75	*Lowest value threshold at poverty line of 26,200 for a family of four*
Land Surface Temperature	0 to 5 to 0	0 to 37 to 0	*Maximum values at central LST values; minimized values at coolest and hottest areas.*

Weighted Sum

All reclassified rasters were input into a single weighted sum for final integration into the cost surface. Weights were confirmed by the client before being applied to each of the factors according to their designated importance.

Table 3. Factor Weights for Different Input Variables into the Cost Surface

Feature	**Weights**
Distance Rasters	
Distance to Managed Area	1
Distance to Natural Area	1
Distance to Wetland	1
Distance to Trail	0.5
Distance to Road	0.75
Distance to Transmission line	0.75
Distance to Water Line	0.5
Distance to Sewer Line	0.5
Discrete Rasters	
Biodiversity	2
Wetlands	1
Median HHINC	1
Land Surface Temperature	1

Finally, a polygon version of the cost surface was also developed at the county level. The continuous raster surface was reclassified into 5 discrete categories and converted into a polygon feature class.

Results

The final cost surface products consisted of continuous raster layers for Durham County, a polygon version of the county-wide cost surfaces, and raster layers for each of the three sub-sectors (Braggtown, East Durham, and Lowes Grove), These products severed as the basal level for analysis, and were extrapolated to parcel layers for further comparison. At the client's request, a flow-chart of developmental steps was also created for potential dissemination of the products to other technicians wishing to replicate our process.

Summary statistics for each cost surface are displayed in Table 4. The range of values for each of the surfaces differs based on locational inputs. Notably, the overall range of values for the county-level cost surface differs from that of the individual sector layers due to the greater reclassification scale (the reclassified values for the county-level inputs were increased to match the increased map scale).

Table 4. Summary Statistics of Cost Surfaces by Sector

Sector/Area	Mean	Median	S. Dev.	Min	Max	Skew	Kur
County	427.84	444.75	80.52	118.5	609.25	-0.70	2.74
Braggtown	58.09	59.50	10.34	17.25	80.5	-1.11	4.39
East Durham	58.82	61.25	11.70	27.25	79.25	-0.63	2.31
Lowe's Grove	62.47	65.00	11.28	28.50	84.25	-0.81	3.01

County-Level Products

At the county level, the weighted sum, here "Development Suitability Score" ranges from 118.5 to 609.25, with higher values shown in darker greens. The layer (and all other depictions of raster cost surfaces) are symbolized with a minimum-maximum stretch.

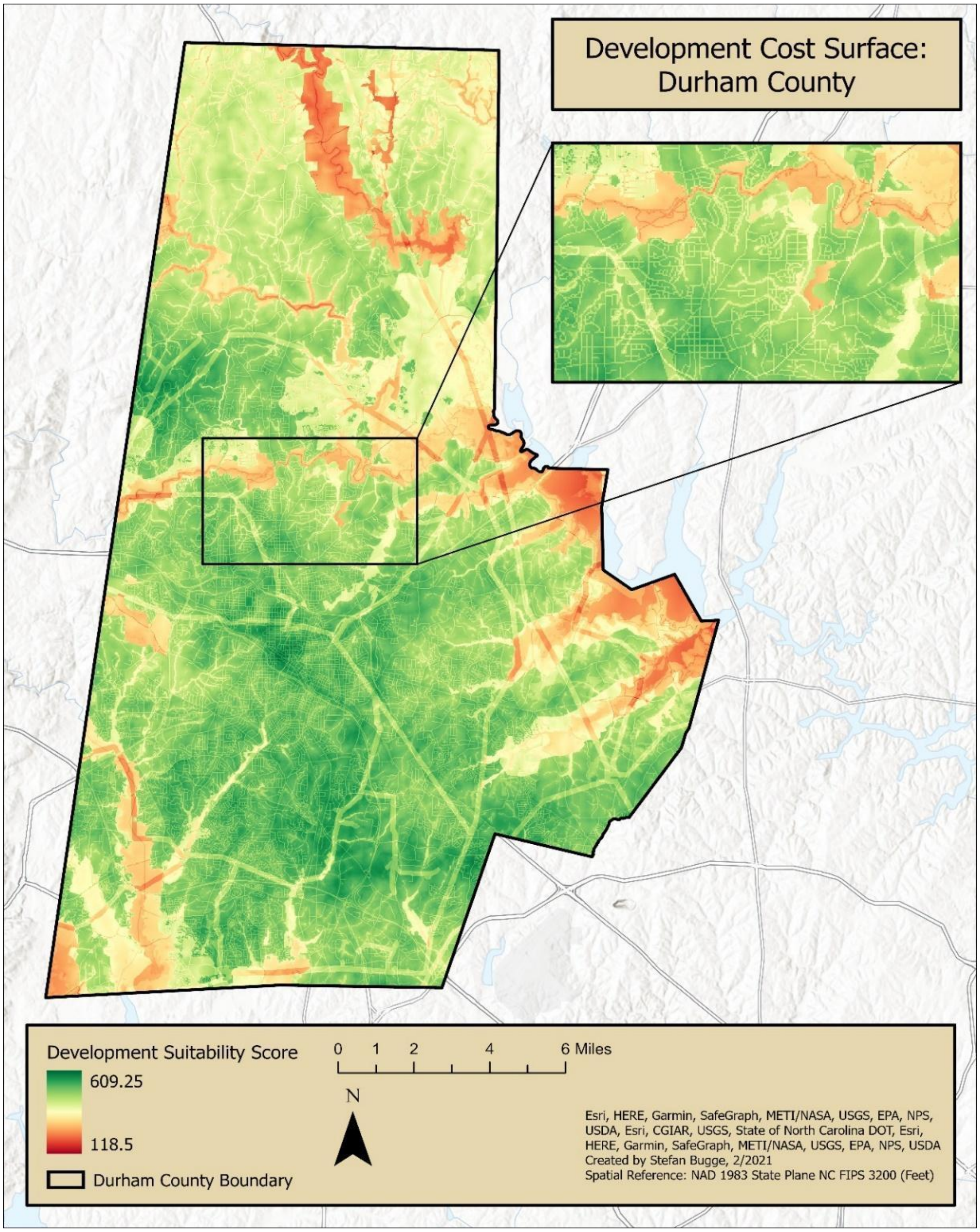

Figure 1. County-Level Development Cost Surface

The polygon-level surface offers a stratified interpretation of the continuous layer. Values were categorized into 5 broad levels of development suitability, with “1 - Never Develop / High Priority Conservation” representing the lowest suitability and “5 - Optimal for Development” the highest. Levels were generated using Jenks Natural Breaks.

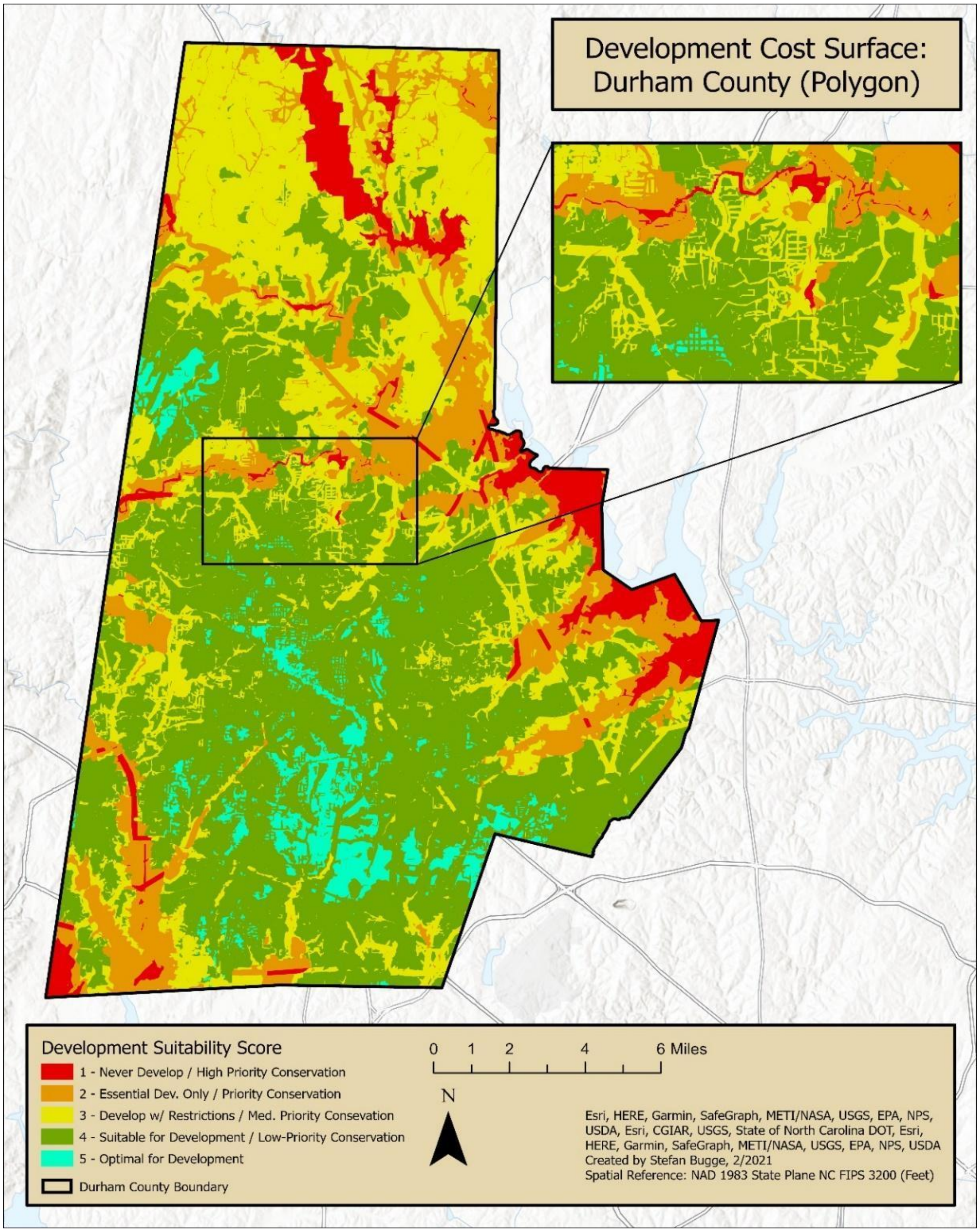

Figure 2. County-Level Development Surface (Polygon)

Sector-Level Products

Figure 3 depicts the three exploratory sectors for which the cost surfaces were initially generated. While the scales for each differ slightly, values overall range from 17.25 to 84.25.

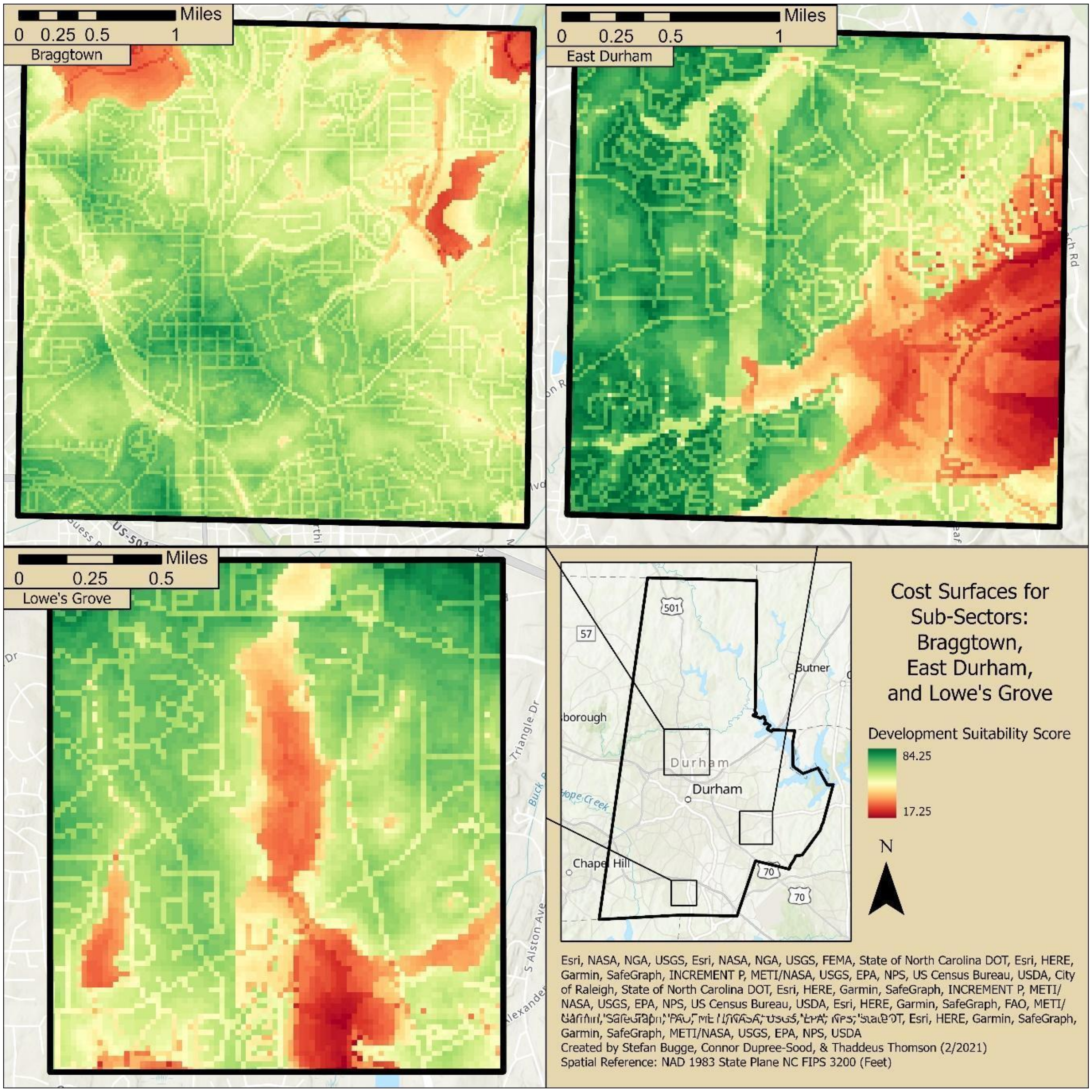

Figure 3. Development Cost Surfaces at the Sector Level

Flowchart of Process for Distribution to Stakeholders

One of the requested deliverables of this product was a simplified flowchart illustrating the analytical steps in producing a final cost surface, so that the process might be carried out at different scales by interested parties. The flowchart presented here represents the cost surface process in simplified form and was workshopped with conservation NGOs in January 2021. A more detailed rundown of analysis, including ArcGIS Pro models and Google Earth scripts can be found in the appendices to this paper.

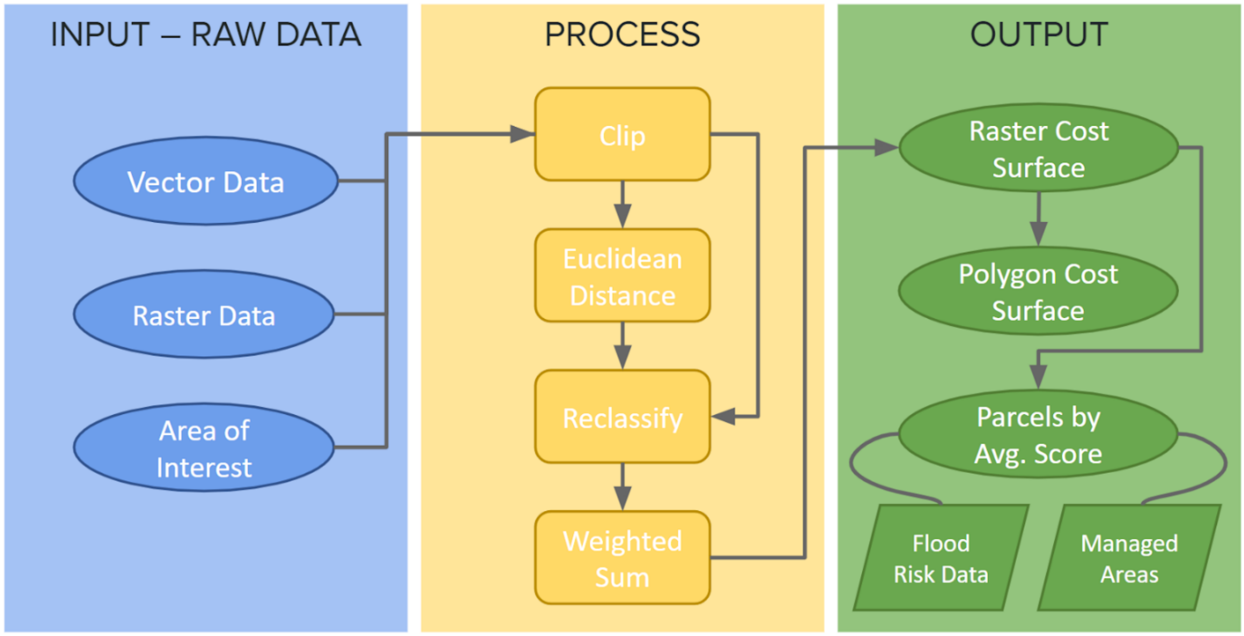

Figure 4. Flowchart of Simplified Models

Discussion

Cost surface products included in this project are useful tools for approximating the suitability of areas for development and conservation. They synthesize relatively disparate data inputs, chosen based on consultation and expert analysis, and provide a basis for educated guesswork. In addition to providing a foundation for general analysis, these products can be applied to more specific analyses (see part V for an examination of cost surface data at the parcel level).

We primarily envision these products being used as a starting point when selecting an area for development or conservation. A city planner or NGO might use the surfaces to select a focal area for further in-depth analysis, or to rule out certain areas as incompatible with organizational objectives. To maximize utility, clear presentation of input variables and transparency in the analytical process are critically important to provide end-users with the requisite understanding of the model's extent and limitations. For example, a conservation planner might benefit from understanding the cost surface's substantial weighting of wetland features; a city planner or developer would be able to make a more informed decision with understanding of the buffering regions around roads, trails, and power lines. To this end, this section seeks to present the study's limitations as completely and accurately as possible.

While we are confident in the overall utility of the products, they should not be considered authoritative for a number of reasons. Several caveats and potential sources of error are discussed in the following sections.

Limitations of the Data

This project incorporates many distinct layers from disparate sources, and while efforts were taken to acquire the most contemporary and precise data available, several issues arise from the incorporation of incomplete or out-of-date information.

In several cases, the best available data that also fell within our accessibility criteria (free and open access) were not current. Our result is therefore a product of data spanning a multi-decadal range, with inaccuracies related to dated or temporally misaligned input features. While we do not expect these inaccuracies to skew the results for use in the short term, issues related to data longevity are only expected to grow over time. An evolution of this project would ideally incorporate annually updated data alongside rapidly updated sources of remote sensing data to ensure accuracy. A product is only as "up to date" as its most recently acquired product; this product is appropriate for general estimates of ground truth, but with more contemporary inputs it could reliably act as a monitoring service.

The derived wetlands raster layer exhibits limitations related to raster cell size. Both input rasters were derived from Landsat 8 imagery with a 30-meter resolution. At the spatial scale under consideration, Landsat 8 imagery frequently distorted or excluded wetland and water features smaller than 30x30 meters. While the layer captures the spatial footprint of larger and more ecologically critical wetland features, exclusion of narrow riverine systems and smaller ponds and retention features reduces the overall accuracy of the layer.

A potentially more serious issue with the cost surface product relates to omission of data: inputs not included due to oversight or lack of availability. Data were chosen for inclusion based on a-priori assessment of contributing factors and consultation with the client and other experienced sources such as non-profit conservation groups. However, the model could still be improved through incorporation of additional information. For example, several new priorities were identified late in our analysis (through conference with the client and stakeholders) that were not fully integrated into the cost surface model. While these factors, which include flood risk slopes and recently rezoned parcels were accounted for in ancillary analyses (see section V's discussion of overlays), these data represent factors that should have been scored in the final surface but were not due to time and resource constraints. The final surface is a cumulative consideration of a number of factors, so while omissions do not inordinately impact the scoring system, they nevertheless represent a source of inaccuracy.

Moreover, further analytical steps could be taken to systematically relate input factors to development suitability rather than relying on expert analysis. Considering these limitations, the model should be applied with its limited context in mind, and any efforts to replicate the techniques and products developed in this project should be sure to incorporate as much context-specific data as possible.

Limitations of the Analysis

The analytical steps taken to generate the final cost surface products are also worth examining; several decisions throughout the development process resulted in potential inaccuracies, reducing the ground-truth potential of cost surface products.

First, potential errors arise from resampling of raster layers. All Euclidean distance rasters were calculated at 30-meter resolution to match several key inputs (land surface temperature and the wetland layer, namely). While 30-meter cells were appropriate for integration of all layers into a working cost surface, the resolution is also relatively coarse when examining fine-scale features, such as roads or trails, which are often only a few meters wide. Moreover, buffers generated around these features, which varied between 10 and 100 meters, were not always accurately represented at 30x30 meter resolution. Generally, issues relating to the choice of a 30-meter cell manifested more significantly at finer scales; reductions of quality and accuracy should be taken into account when examining focused areas of the map, or when specifically working with narrow input features such as roads and trails.

The use of Euclidean distancing as a proxy for different natural and manmade processes raises questions of accurate representation. While the method provides a simple and streamlined approach to gauging proximity-based impacts, the model may fail to capture nuance in more complex processes. For example, while simple Euclidean distance from wetland features is useful for buffering impacts from development, it fails to accurately represent physical interactions such as runoff, which depends more on terrain and elevation than linear distance from a water feature. These types of error could be rectified by adding processing steps; deriving our wetland distance layer from a flow accumulation layer would provide a more accurate assessment of impact radii for effects such as runoff. Ultimately, in order to limit the model's complexity and promote replicability, these more granular determinations were avoided (but should be considered for application at small scales).

The largest systemic source of uncertainty with our cost surface generation was the use of reclassification functions to reduce inputs such as Euclidean distance and variously ranked raster layers (e.g., our biodiversity layer) into a single scale for the purposes of summation. Use of reclassified inputs allowed recombination of distinct and varied input factors into a single layer, but such simplification came with costs. First, reclassification necessarily reduces information present in its input layers; granularity present in the original data is lost when reclassification occurs (depending on the number of final classes). Reclassification is a tradeoff whereby informational content is exchanged for increased interpretability of results.

Second (and perhaps more importantly), reclassification schemes may not accurately reflect the relationship between the feature in question and development suitability. Reclassification schemes were determined after lengthy discussions between group members and the client, but still represent best estimates of the predicted effects of input factors on development. As with the incorporation of input layers into the model, reclassification would also benefit from a systematized approach based on statistical inference rather than simple expert designation.

Limitations of the Interpretation

With these issues in mind, cost surface products are best suited for preliminary site assessment and estimation of suitability. Areas scoring particularly high or low in the cost surface should be examined by experts, field units, or assessors with site-specific knowledge to confirm the characteristics suggested by the model, and to contextualize the results with more specific information. Assessment should be conducted not only to account for site-specific factors not captured by the model, but also to mitigate potential misclassification by the system.

In Section V we narrow the focus of these products to the parcel level, improving their utility; in Section VII we discuss how the model might be applied at a small scale, examining the Braggtown area of Durham to illustrate the applicability of the toolset.

V. Determination of Suitable Parcels

Introduction

While our continuous and categorical surfaces offer a broad-scale metric for development and conservation suitability in Durham County, we identified applicability as a key priority in our products, and cost surfaces alone not were not deemed sufficient to empower decision makers in a development planning context.

Parcel boundaries have long stood as the most granular unit of city planning, and as they are modified and rezoned frequently, also serve as proof of the ongoing pace of development. Parcel data from 2020 were incorporated into the analysis to better evaluate the spatial relationship of existing administrative boundaries to the established cost surfaces.

Methods

Parcel data for 2020 were obtained from Durham's open GIS as a shapefile and integrated into the GIS.

While the parcel data cover the entire extent of Durham County, only the parcels that had not been fully developed were deemed relevant to the application of the cost surface. To isolate undeveloped parcels, national impervious surface data were obtained from the Multi-Resolution Land Characteristics Consortium National Land Cover Database products (MRLC, 2016). Data were clipped to Durham County and Zonal Statistics were calculated using the Impervious Surface data and existing parcels. Average percentage impervious surface was calculated for each parcel and collated to the attribute table.

Parcels that exhibited less than 10% average impervious surface were deemed "undeveloped". From this sub-category of county parcels, two new shapefiles were generated: one containing undeveloped parcels of two acres or greater (for conservation concerns), and one detailing parcels of five acres or greater.

Using the cost surface layer generated previously, zonal statistics were applied to average the development score across all parcels in the >2 and >5-acre shapefiles, resulting in two comprehensive datasets of undeveloped parcels in Durham County.

Overlay of Managed Areas

By request of the client and in response to feedback obtained in stakeholder meetings, additional changes were made to the two parcel layers to improve their utility for conservation and development prioritization. Managed areas were applied as an overlay to demonstrate which parcels were already under management by federal or non-profit organizations. The Managed Areas layer was the same used in the cost surface calculation and includes information on managing organization and management type. Data from the managed areas layer was also collated to the attribute tables of the parcel shapefiles.

Overlay of Flood Priority Parcels

An additional layer focusing on flood risk was also requested to emphasize parcels in high flood risk zones, as well as those that would increase flood risk to low-lying parcels if developed. This analysis was specifically requested as an overlay, separate from the cost surface layer.

Two sources of data supplied the analysis: FEMA's National Flood Hazard Layer (North Carolina's Spatial Data Download, 2021) and a 25% Slope or Greater shapefile from Open Data Durham. Areas of high slope within a certain distance of the high-risk flood areas were isolated. High risk flood areas were assigned based on flood insurance risk codes designating mandatory insurance A, AE, A1-30, AH, AO, AR and A99. As FEMA does not have any specific recommendations for construction on slopes near high flood risk areas, we conservatively chose 150 meters (492 feet) as the distance within which slopes were designated high risk.

A buffer was generated around the high flood risk areas and intersected with the slopes to produce an overlay of slopes within and adjacent to flood risk zones. The Summarize Within tool was then applied to the shapefile alongside parcel data to limit the parcel layers to those with more than 300 ft2 (27.8 m2) of high-risk slopes intersecting. This minimum area was chosen to omit parcels with minimal slope area.

Overlay of Parcels Proposed for Rezoning in 2020

Additional changes to the parcel layers were made after receiving feedback from local conservation organizations Triangle Land Conservancy, Eno River Association, and Ellerbee Creek Watershed Association (Margaret Sands, Kim Livingston, and Rickie White, personal communication, January 29, 2021). One suggestion was the inclusion of parcels currently undergoing or requested for rezoning, as these parcels represent the areas experiencing the highest levels of development pressure. Rezoning data were obtained from the City of Durham in the form of zoning request maps (City of Durham, 2020).

ArcGIS location tools were used to pinpoint each address and cross-reference the rezoning maps with the existing parcel layers. For each layer (both the >5-acre and >2-acre layer) parcels were flagged if they were proposed for rezoning in 2020. Flagged parcels were then exported into a new layer for use as an overlay. A single, comprehensive priority layer was derived from the 2-acre parcel layer, as it necessarily included all of the parcels within the 5-acre layer as well.

Summary Statistics

For both datasets (greater than 2 & 5-acre parcels, respectively), ArcGIS built-in tools were used to calculate summary statistics of parcel size, percent impervious surface, and average development score based on the integration with our cost surface layer. Parcel summary statistics are displayed in the Results section of this report.

Numbers were also derived from the managed areas layer; by intersecting managed areas with the parcel layers, it was determined how many parcels of each development score class were already under management. These numbers were cross-referenced with the development "code" for each parcel to obtain the percentage of each development tier already under management. Finally, counts of priority parcels (those proposed for 2020 rezoning) were also recorded per development class.

Results

Parcel products consisted of two separate layers, one representing undeveloped parcels greater than 2 acres in size (as requested by the client), and a second representing undeveloped parcels of 5 acres or more. Parcels were coded with mean values from the cost surface layer and are displayed according to their suitability for development. Summary statistics for each parcel dataset are displayed in tables 5 and 6; figures 5 and 6 follow.

Table 5. Summary Statistics for Key Variables, Parcels Greater than 5 Acres (n = 3994)

	Mean	**Median**	**S. Dev.**	**Min**	**Max**	**Skew**	**Kur**
Area (Acres)	26.26	11.72	76.79	5	3,410.64	26.43	1025.32
Avg % Impervious (across entire parcel)	0.8774	0.129	1.794	0	9.967	2.953	11.75
Avg Development Score	421.96	432.15	66.38	203.72	572.93	-0.59	2.82

Table 6. Summary Statistics for Key Variables, Parcels Greater than 2 Acres (n = 7605)

	Mean	**Median**	**S. Dev.**	**Min**	**Max**	**Skew**	**Kur**
Area (Acres)	15.25	5.248	56.84	2	3,410.64	34.77	1820.02
Avg % Impervious (across entire parcel)	1.076	0.193	1.917	0	10	2.466	8.93
Avg Development Score	434.46	443.95	62.7	203.48	584.95	-0.72	3.29

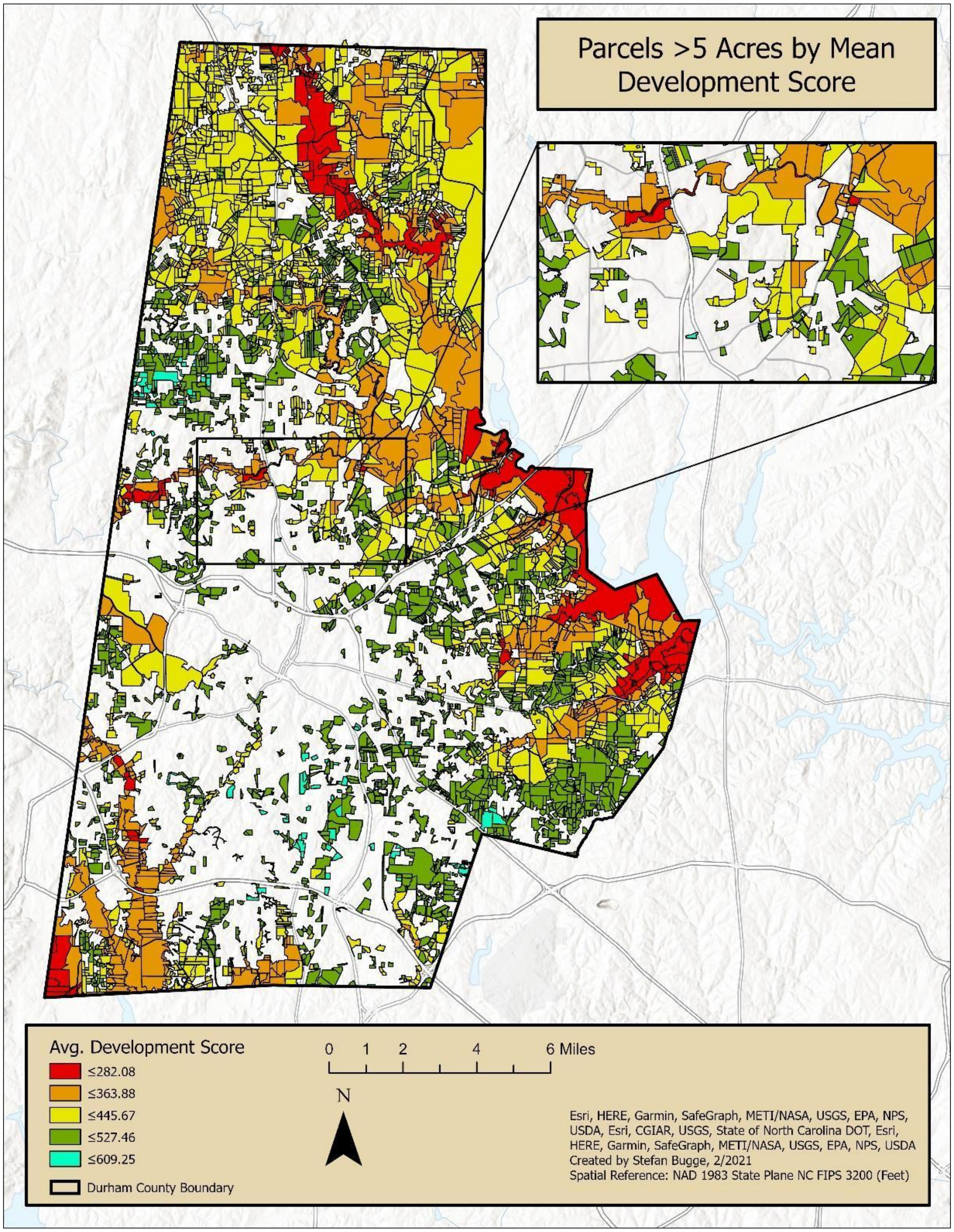

Figure 5. Parcels Greater than 5 Acres Coded by Mean Development Score

Parcels in redder tones in the two figures exhibit low development scores, meaning they incorporate factors that are either important for maintenance of ecosystem services, or they lack factors that make them suitable for development. Conversely, green and teal parcels are deemed more suitable for development by the model: they exhibit fewer characteristics identified as critical to maintaining ecosystem services, and they are in proximity to factors that facilitate development, such as existing utility lines or roads. While the development score does not strictly recommend development based on high values, it suggests that these parcels would exhibit the least environmental impact, and best encourage nodal city structure were they developed.

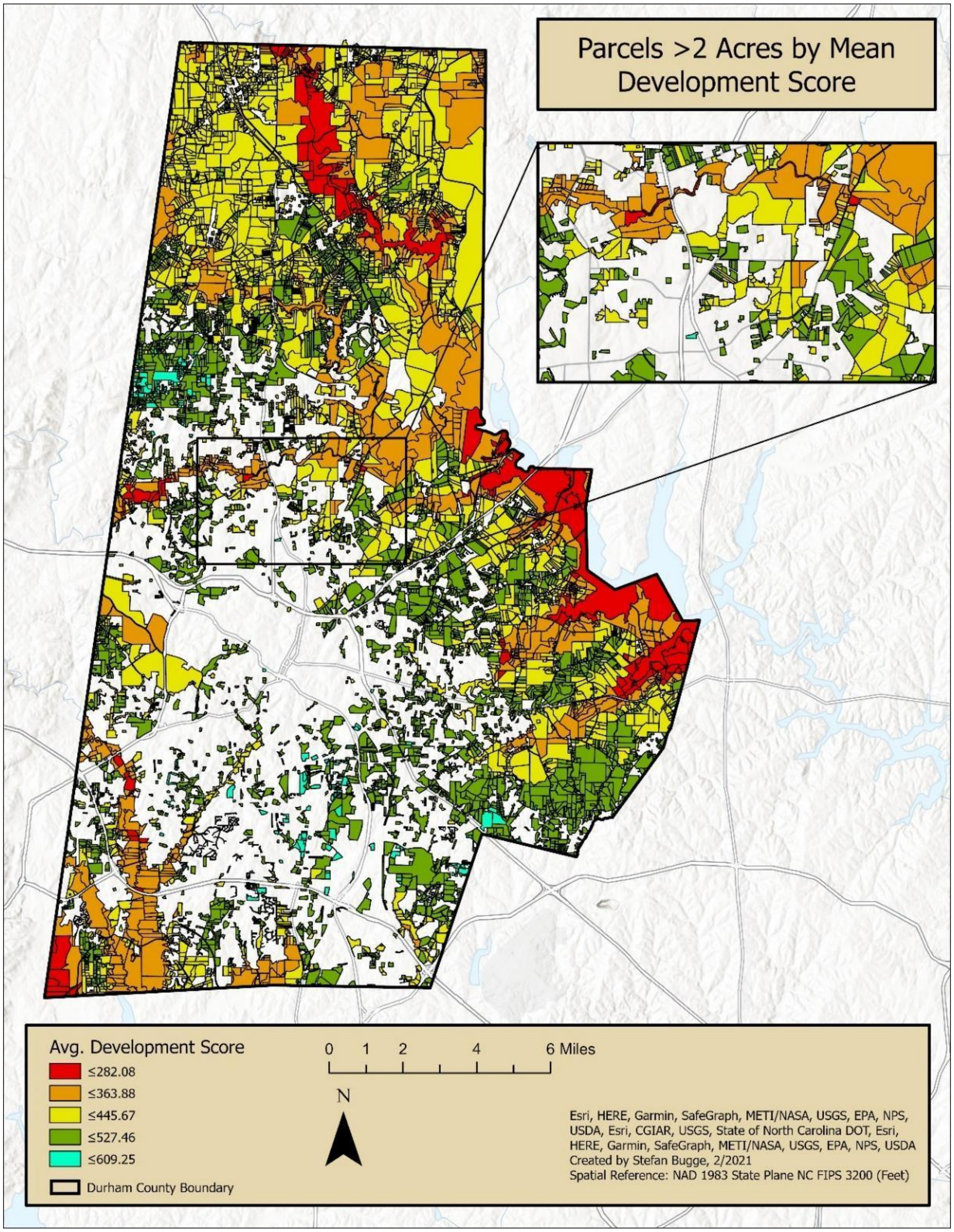

Figure 6. Parcels Greater than 2 Acres Coded by Mean Development Score

Managed Areas & High Priority Parcels

Managed area data were projected over parcel data to show which parcels were exempt from development concerns; applying this layer also offered insights into the functionality of our system.

Parcels that were requested for rezoning in 2020 were also identified and added to the GIS as an overlay. These parcels represent the areas currently under development or most likely to see development in the near future and provide insight into general development trends as well as specific conservation priorities.

1135 of 3994 parcels greater than 5 acres, and 1481 of 7605 parcels greater than 2 acres were already under management at the time of this study. 35 of the 3994 parcels greater than 5 acres, and 51 of the 7605 parcels greater than two acres were requested for rezoning in 2020. Figure 7 displays managed areas and high priority parcels overlaid with undeveloped parcels greater than two acres. Tables 7 and 8 show the counts of parcels falling within each development category, as well as how many of each category fell within managed or priority zones.

Table 7. Parcels Greater than 5 Acres per Development Score Category

	Total	**DS1**	**DS2**	**DS3**	**DS4**	**DS5**
Count Parcels >5	3994	145	612	1596	1552	89
# managed	1135	125	465	418	126	1
% managed	28.42	86.21	75.98	26.19	8.119	1.12
# Priority	35	0	7	7	21	0
# With Flood Risk	1,219	119	375	450	262	13
Slopes ($\geq$ 300 ft^2)	(1,286.38 acres)	(308.51 acres)	(541.85 acres)	(330.72 acres)	(102.88 acres)	(2.42 acres)

Table 8. Parcels Greater than 2 Acres per Development Score Category

	Total	**DS1**	**DS2**	**DS3**	**DS4**	**DS5**
Count Parcels >2	7605	180	852	2855	3446	272
# managed	1481	146	564	578	192	1
% managed	19.47	81.11	66.20	20.25	5.57	0.37
# Priority	51	0	8	12	29	2
# With Flood Risk	1572	148	456	582	370	16
Slopes ($\geq$ 300 ft^2)	(1,366.39 acres)	(319.36 acres)	(575.12 acres)	(351.26 acres)	(118 acres)	(2.67 acres)

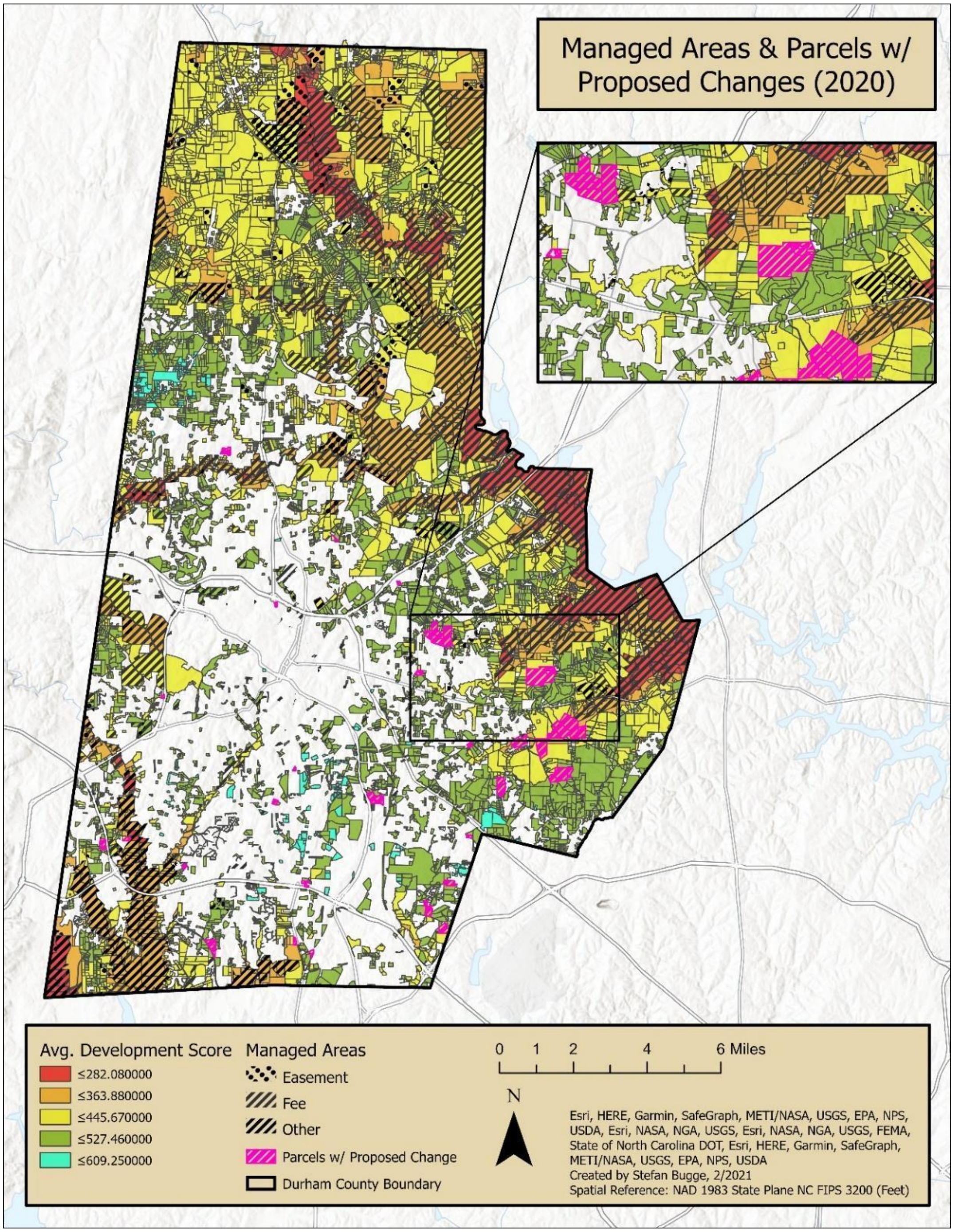

Figure 7. Managed Areas & Parcels with Proposed 2020 Changes Overlaid w/ Parcels Greater than 2 Acres

Flood-Risk Conservation Priority Areas

As requested by the client, parcels that could lead to increased run-off to high flood risk areas if developed were highlighted in an additional overlay. Slope-related statistics were calculated for all parcels (Table 7 and Table 8). 20% of parcels greater than 2 acres and 30% of those greater than 5 acres intersected with flood risk slopes. Development score 3 ("Develop w/ Restrictions") exhibited the most at-risk parcels, followed by 2, 4, 1 and 5. Proximity to wetlands tends to indicate flood risk and was also a negative influence on a parcel's development score; the distribution of flood risk parcels was spatially concentrated near riverine features and lakes, along the northeast and southwest edges of Durham County and spreading into the center.

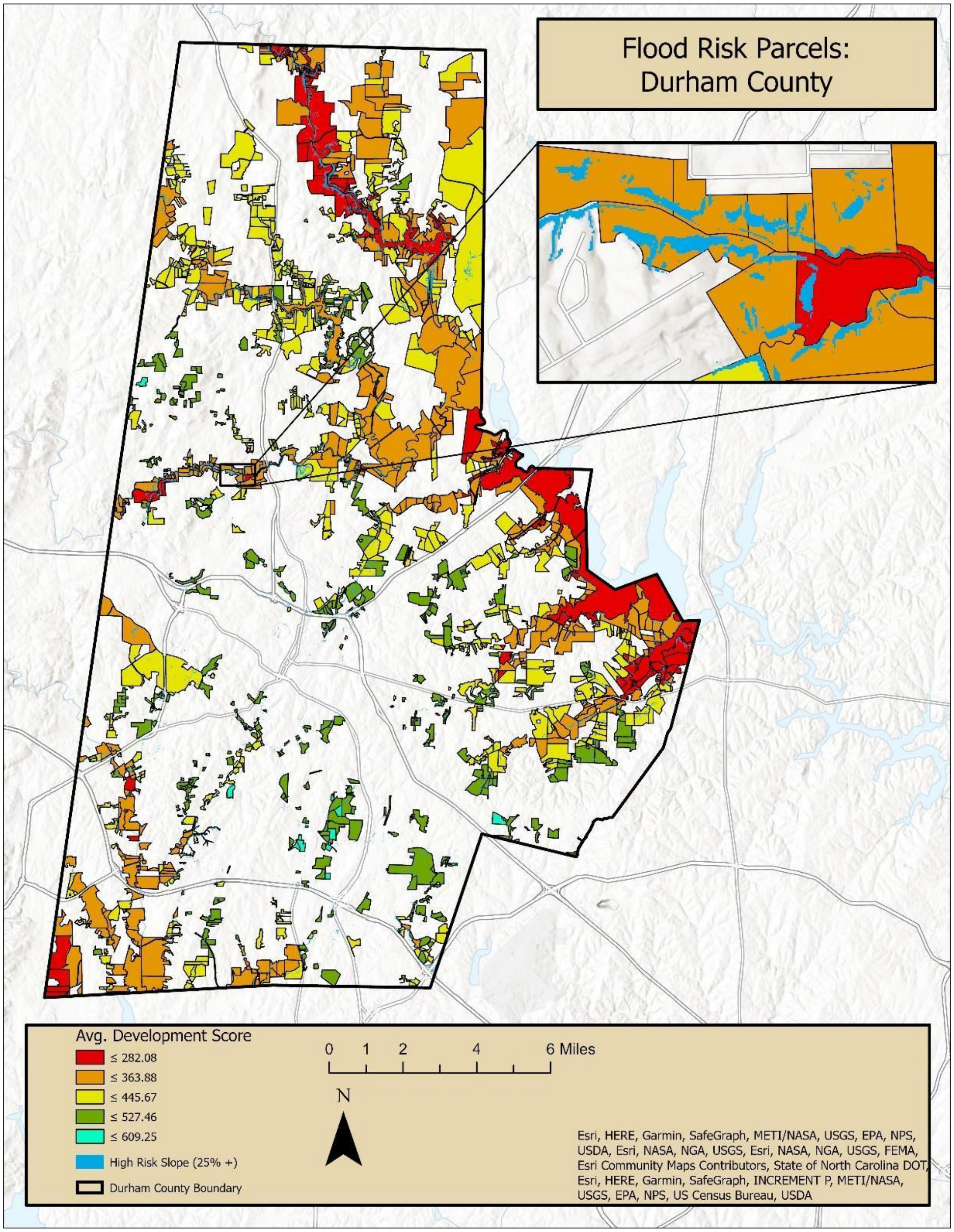

Figure 8. Parcels Greater than 2 Acres Containing Flood-Risk Slopes

Analysis of Habitat patches - Eno New Hope Landscape Conservation Project

Discussion with Kim Livingston of the Eno River Association led to the examination of several resources that could be useful in our analysis. One of those resources was the Eno New Hope Landscape Conservation Project (Tuttle et al., 2019). We examined the project's habitat patches layer, which showed suitable patches for development-sensitive species. Although the dataset was not comprehensive across the county and thus not relevant to our cost surface analysis, it was used for comparative analysis where it intersected parcel layers.

While the two layers have different scoring systems and are thus limited in comparative power, the result of their intersection is useful for determining if our products were aligned with those of other conservation projects in Durham County.

Data were clipped to Durham County and intersected with parcels greater than 2 acres. Table 9 enumerates the relationships between development scores (1 lowest to 5 highest) with habitat patch priority scores (1 highest to 5 lowest).

Table 9. Area (sq. mi.) and % of Habitat Patches in Durham County intersecting Parcels > 2 Acres

Habitat Patch Priority	Total	DS1	DS2	DS3	DS4	DS5
1 - Highest	18.38	1.83	15.29	1	0.24	0
	95.12%	9.49%	79.2%	5.18%	1.25%	
2 - Higher	16.51	2.92	6.59	5.46	1.51	0.03
	96.15%	17.01%	38.40%	31.79%	8.81%	0.15%
3- High	20.45	1.04	12.89	4.82	1.29	0.41
	93.03%	4.74%	58.66%	21.93%	5.85%	1.86%
4 - Moderate	45.89	0.93	19.11	18	7.22	0.63
	92.05%	1.87%	38.33%	36.12%	14.47%	1.26%
5 - Unranked	13.75	0.014	0.96	4.66	7.59	0.52
	89.71%	0.09%	6.28%	30.42%	49.55%	3.36%

90% or more of the habitat patches for each priority level intersected with existing parcels. Of the highest priority patches, 80% intersected with patches with a Development score of 2 or lower. Higher and high priority levels (2 and 3, respectively) both had 80% of patches intersect with parcels that had a development score of 3 or lower. For moderate and unranked priorities, the majority of habitat patches occurred within development score 3.

Discussion

Parcel products offer an additional layer of accessibility and utility, deploying the results of our cost surface analysis at a spatial scale relevant to both development and conservation needs. The reduction of cost surface products to the parcel level also allows for comparative analysis between known features, such as areas managed for conservation, with analytical outputs. Parcel-level products adequately represent trends of conservation and development within Durham County. Even so, Parcel products are subject to several sources of potential error that could confound their utility, especially in the long term.

Accuracy Assessment

In the absence of ground-truth data allowing for a full-scale accuracy assessment, data describing existing conservation features were applied in order to gauge the propensity of our model for accurately selecting high priority conservation areas and zones of development. Although this comparative analysis provides a less-robust examination than a fully ground-truth supported accuracy assessment, resultant metrics provide a general estimate of how well the development scores generated by our cost surfaces represent trends in conservation and development.

In parcels greater than 2-acres (our most comprehensive data layer), existing managed areas tended to be appropriately reflected by the development scores of their containing parcels. Of parcels scoring a "1" (designated by cost surface value averaging less than 282 over the parcel's area), 81% were already in management; for development score "2", 66% were already managed, and for development score "3", 20% of parcels were under conservation management. Across all development scores, the percentage of parcels under management increased with decreasing score. This trend aligns with the model's goal of discouraging development and encouraging conservation in areas with the lowest scores, and generally suggests that our model aligns with the priorities of organizations such as the groups we consulted with that are already conducting management of sensitive areas in Durham (Triangle Land Conservancy, Eno River Association, and Ellerbee Creek Watershed Association). This trend also suggests adopters of the model would be best served by examining parcels scored in categories 1 & 2 that are not currently under management.

Table 10. Managed, Priority, and Flood Risk Areas within Parcels Greater than 2 Acres

	Total	**DS1**	**DS2**	**DS3**	**DS4**	**DS5**
Count Parcels >2	7605	180	852	2855	3446	272
# managed	1481	146	564	578	192	1
% managed	19.47	81.11	66.20	20.25	5.57	0.37
# Priority	51	0	8	12	29	2
# With Flood Risk	1572	148	456	582	370	16
Slopes ($\geq$ 300 ft^2)	(1,366.39 acres)	(319.36 acres)	(575.12 acres)	(351.26 acres)	(118 acres)	(2.67 acres)

Similarly, we examined the number of parcels undergoing the rezoning process in each development score category to gauge how well our model predicted propensity for development and found a trend inverse to that seen with managed parcels. Development scores "4" and "3" had the highest number of parcels with recent re-zonings, and the percentage decreased with decreasing development score. Development score 5, however, only contained two undeveloped parcels with rezone requests.

While the trend generally aligns with our model's goals (higher development scores see more development), the minimal number of parcels in category 5 indicates that the model does not align perfectly with patterns of development in Durham. Even so, this trend should be taken with a grain of salt, as the sample size of rezoned parcels in 2020 (51 of 7605) was much smaller than the number under management (1481). Moreover, these rezoning requests do not always signify development, and can be indicative of other changes in land use. Overall, they offer a fairly nebulous understanding of the ongoing progress of development in 2020 and provide only a cursory assessment of our model's accuracy.

As these trends suggest, our model aligns with both conservation and development concerns to a reasonable degree, but the results are still prone to error and lack context-specific information. A full-scale accuracy assessment using ground-truth data or high-resolution satellite imagery would be a step towards better utility, allowing us to better gauge the applicability of the model. Thus, while parcel-level products provide utility beyond that of the simple cost surface, they should still be applied alongside localized knowledge and survey of target areas.

Limitations of the Data

Several issues with parcel data and the data acquisition process generate sources of inaccuracy or error in the final parcel dataset, especially over time.

First, parcel data are prone to constant change as properties are sold, redeveloped, or rezoned. Durham's pace of development is rapid, and the analysis conducted here will maintain relevance for only a few years before requiring updates. Ideally, updates would co-occur with Durham County and City's municipal reporting of rezoning, so as to capture changes in parcel boundaries and ownership as they occur.

Parcel data are also a relatively poor indicator for in-progress development. They include only minimal information regarding changes in projected land use, and in many cases only shift to accurately represent changes in ownership or development after decisions have already been made. We offer a partial remedy to this issue with our high-priority parcel layer, which emphasizes parcels requested in the past year for rezoning. However, a more systematic approach to monitor proposals in advance of development actions would extend the utility of our parcel products.

Lastly, National Land Cover Data describing impervious surfaces, while comprehensive, are several years out of date (with the most recent release in 2016). Because we used these data to designate parcels as "undeveloped" (<10% impervious surface), current parcels that have already undergone construction or land changes are possibly mistakenly classified. While NLCD is a superb resource for tracking imperviousness at large scales, with the pace of development, a more contemporary or localized data solution would help improve the longevity of the model.

Issues with our parcel data suggest the use of real-time data would drastically improve the model. In a perfect world, data would be fed contemporaneously into the model to track parcel status, impervious surface, land use, and development score. Such a system would provide enormous utility to city planners and land managers but would demand access to data that (as of yet) are not easily or publicly accessible.

Limitations of the Analysis

Several steps in the parcel generation process were sources of potential error.

Parcels were considered undeveloped if they exhibited an average impervious surface of less than 10%. This percentage was chosen based on applications of several different percentages and visual assessment of the results; 10% provided a more consistent result than 15%, while still including parcels that were partially developed but contained significant forested elements. While the 10% cutoff was suitable for the purposes of this project, it captured areas such as athletic fields that were already under “developed” use (not impervious, but also not relevant to the analysis). Second, the use of zonal statistics to capture the mean impervious surface of parcels necessarily reduced the information present in the initial input layers. Although this technique allowed integration of imperviousness data into a parcel-wide measure, it also tended to misclassify highly heterogeneous and large parcels - for example, a parcel divided evenly between forest and developed buildings would not be recognized by our model as having any conservation value, even if it contained a large tract of intact forestland.

While tweaking the 10% cutoff would make the model more accepting of heterogeneous parcels, it would also reduce the selectivity of the model. A more robust analytical tool, such as supervised or object-based classification might be applied to capture the contents of parcels in as finer detail; however, for the extent of this analysis, the solution was deemed effective enough.

Flood risk analysis was also prone to limitations that limit the layer’s descriptive power. The flood risk overlay was added late into the project upon special request of the client. While use of a county-wide Digital Elevation Model (DEM) would provide the most accurate assessment of slope for the purposes of prioritizing areas adjacent to flood plains, the NC Spatial Data website only provided DEMs in small batches aligning to a county-wide grid. The time needed to mosaic them together into a county wide DEM precluded use of this approach; instead, we chose a shapefile provided by Durham County GIS that contained all slopes of 25% or greater within the county. Without using a DEM, we could not expand into further hydrological analysis, such as flow accumulation and direction, nor select our own threshold for slope steepness. Time constraints also prevented the integration of the flood risk layer into our main cost surface. Lastly, FEMA does not provide guidelines for proximity between high flood risk areas and areas with steep slope, so risk distance from flood zones (150 meters) was calculated to capture the highest number of slope polygons within adjacent parcels.

The comparison of parcel development scores to the Eno New Hope Landscape Conservation Project’s habitat patch layer was also conducted late in the project and has several limitations. Because the habitat patch layer did not encompass the entire county, it could not be integrated into the cost surface. This spatial discrepancy also resulted in limited comparative power; habitat patches could only be compared to parcel results in the central area of the county.

VI. Walkability

Introduction

Walkability simply refers to the ease with which people can walk to and from desired locations. For this project we further define an area as walkable if it is safely and easily accessible by foot and within 1 mile of a pedestrian's starting location. Improving walkability within cities, towns, and neighborhoods is a growing trend across much of the United States, and provides significant health, environmental, communal, and financial benefits.

This case study takes place in Braggtown, a primarily African American neighborhood in north Durham. Originally it was a self-reliant Black community, largely made up of individuals who traveled there after being freed from the Stagville plantation in the 1800s. The area was later annexed by the City of Durham in the late 1950s but remained in isolation until the 1960's when the creation of I-85 formed the first paved road joining the two. This location was chosen for analysis for a multitude of reasons. From an equity standpoint, minority residents still make up over 80% of the Braggtown population. Median income is also below average when compared to other areas both in and out of the city. From an ecological perspective, Braggtown's average percent tree cover is above that of the county and is home to rare plant species. Residents in Braggtown also experience higher than average health concerns such as diabetes, heart attacks, strokes, and kidney disease. These higher numbers were also consistent across race and across income levels – a potential indication of poor environmental conditions. Lastly, from a walkability standpoint, very few residents reported the ability to walk or bike to work despite Braggtown having above average sidewalk coverage. Given increasing gentrification trends, the fact that the one area in Braggtown that reported higher numbers of individuals walking to work came from the higher income block group (the only majority white group) was unsurprising (Durham Neighborhood Compass, N.D.). Given that more walkable neighborhoods can help preserve valuable ecosystems, improve public health, and reduce travel time and costs, Braggtown appeared to be an ideal location in need of improved walkability.

Methods

Data Preparation

There were no geospatial data available describing a precise boundary of the Braggtown area, so one was manually created. An image of the Braggtown boundary was imported into ArcGIS from DataWorks NC (Killeen, 2019). A new feature class was created using the Create Feature Class tool to manually trace the outline of the image. The resultant polygon boundary layer was then converted to a raster. This raster was used in the following steps to clip other layers to the Braggtown area.

Zoning data for 2020, as well as data for parks (2019), schools (2020), and roads (2020) were obtained from Durham Open Data as separate shapefiles and integrated into GIS. Each layer was then clipped to the new Braggtown boundary. Schools were left as point data, while roads and parks were each converted to a raster dataset. Two new polygon feature classes were created from the zoning data using the select by attribute tool to identify the commercial zones and high-density residential zones within Braggtown. The residential zones served as starting points for the cost path analysis, and the commercial zones served as one of the destination points. The commercial zones layer was further simplified to include only areas with a diverse array of goods (grocery, clothing, discount) and services (banks, postal service). Desirable commercial zones that were adjacent to one another were combined into one zone using the Dissolve tool, resulting in two commercial zones. A point feature class was made for each of the commercial zones, with the point placed in the center.

All six high density residential zones were used. Instead of using the entire polygon for each residential site, a new point feature class was made for each individual site. One of the residential sites was very large so two separate points were used to represent each half of the neighborhood.

Creation of the Cost Distance Surface

A separate cost distance surface was created for parks, schools, and commercial zones. In preparation for the cost distance surface the Euclidean Distance tool was used on the roads raster layer to assign each cell a value based on the distance to the nearest road. Using the Reclassify tool, the distance ranges of the resultant raster were reassigned values from 1 to 6. This reclassification represented a pedestrian's ease of travel across the raster surface in terms of distance to the nearest road. To encourage travel along sidewalks, distances closest to roads were given the lowest value of 1, while the farthest distances were assigned a value of 6. This reclassified distance raster was used as the input cost raster in each Cost Distance tool.

The Cost Distance tool was then used to run the school points (source data) against the reclassified cost surface. This produced a raster surface with each cell containing a distance from itself to the closest school point using the least cost path. Because the Euclidean distance raster was created using distances from roads, the least cost path encouraged movement through the cells closest to walkable roads.

In order to demonstrate all areas within a walkable distance, the Reclassify tool was applied once again to convert the cost distance raster into five classes. The first four represented quarter mile increments, while the last represented distances over a mile (generally considered unwalkable for purposes of this study).

The process detailed above was repeated again using parks and commercial areas respectively as source data; the same reclassified roads distance raster was used for each as the input cost raster.

Creating the Least Cost Path

Three least cost paths were created, each using a selected residential site. The paths show the least cost path from a selected residential site to a park, a school, and a commercial area.

To generate the cost surface for pathing, the original roads raster created during the data preparation phase was reclassified by functional class. This allowed for different weights to be assigned for different road types. However, since all relevant roads had sidewalks, each was assigned a value of 1 and anywhere with no data was given a value of zero. The original parks raster was also reclassified and assigned a value of 1 for each park, as these spaces are completely walkable. To account for surfaces that are less than ideal for walkability, such as woodlands and buildings, 2016 national land cover data were downloaded from MRLC (MRLC, 2016-a). The data was clipped to the Braggtown boundary and used as an input in creating the cost surface.

Since the land cover data were not 100% accurate and sometimes assigned land cover types to areas of existing roads, the Raster Calculator tool was applied to remove road pixels from the land cover raster. This was critical for correctly assigning weights to different land cover types and roads. Different land cover types also overlapped with park space, so parks data were similarly used to mask the land cover raster so that the entire park was correctly classified as walkable. The resultant layer excluded land cover data from where roads and parks are located. The corrected land cover raster was reclassified so that each land cover type was assigned a value between 1 and 10, with 1 representing areas easiest to walk through and 10 representing the most difficult.

The Weighted Sum tool was applied to integrate land cover, roads, and parks. Each raster was assigned an equal weight of 1. The raster produced by the weighted sum was then used as the input cost raster for the Cost Distance tool.

The desired residential site that served as the starting location for the cost path was used as the source point for the Cost Distance tool. Once the output distance and direction were obtained from the Cost Distance tool, they were used in the Cost Path tool along with the desired feature destination data. The school, park, and commercial area served as the feature destination layer in each of the three cost paths run.

Results

This analysis looked at walkability from residential locations to schools, parks, and commercial areas within Braggtown. There are two separate products from this analysis for each pairing: a cost distance layer and a least cost path.

A separate cost distance layer was made for schools, parks, and commercial areas. Each layer displays what areas of Braggtown are within a walkable distance (1 mile) from the selected feature if a resident were to travel only using sidewalks. This 1-mile distance is further divided into quarter mile increments to show more specific distance ranges. Anything located over a mile from the selected feature is shown in red.

Each map displayed below shows both the walkable cost surface as well as an accompanying least cost path. To provide an example of a least cost path, a residential site was chosen to serve as a starting point to one of the feature destinations of interest.

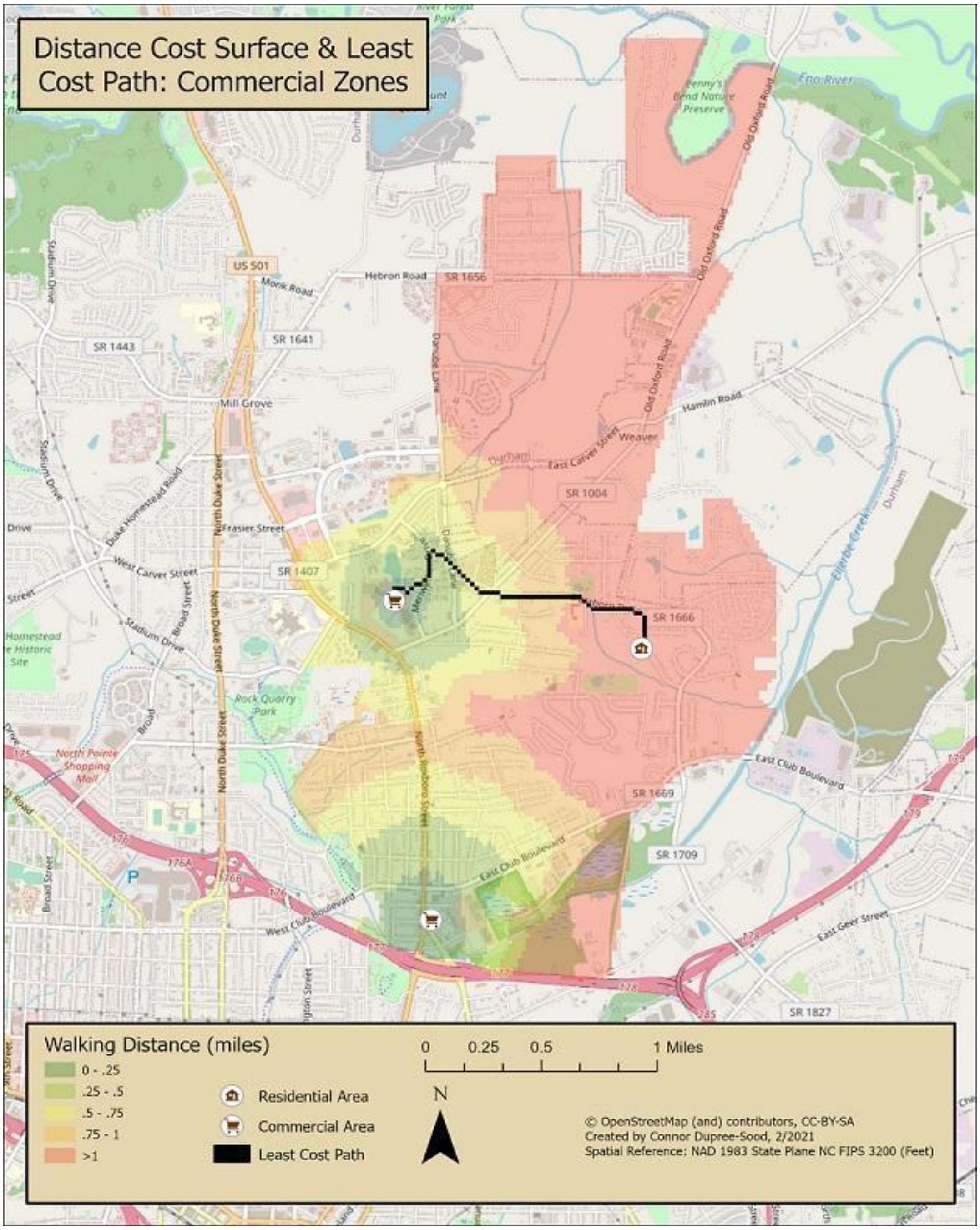

Figure 9. Example least cost path between residential areas and commercial areas in Braggtown

This map displays the walkable area within a mile of the two main commercial zones in Braggtown. The pathway shows the least costly path for a resident if they were to walk to the primary commercial zone from residential site 6.

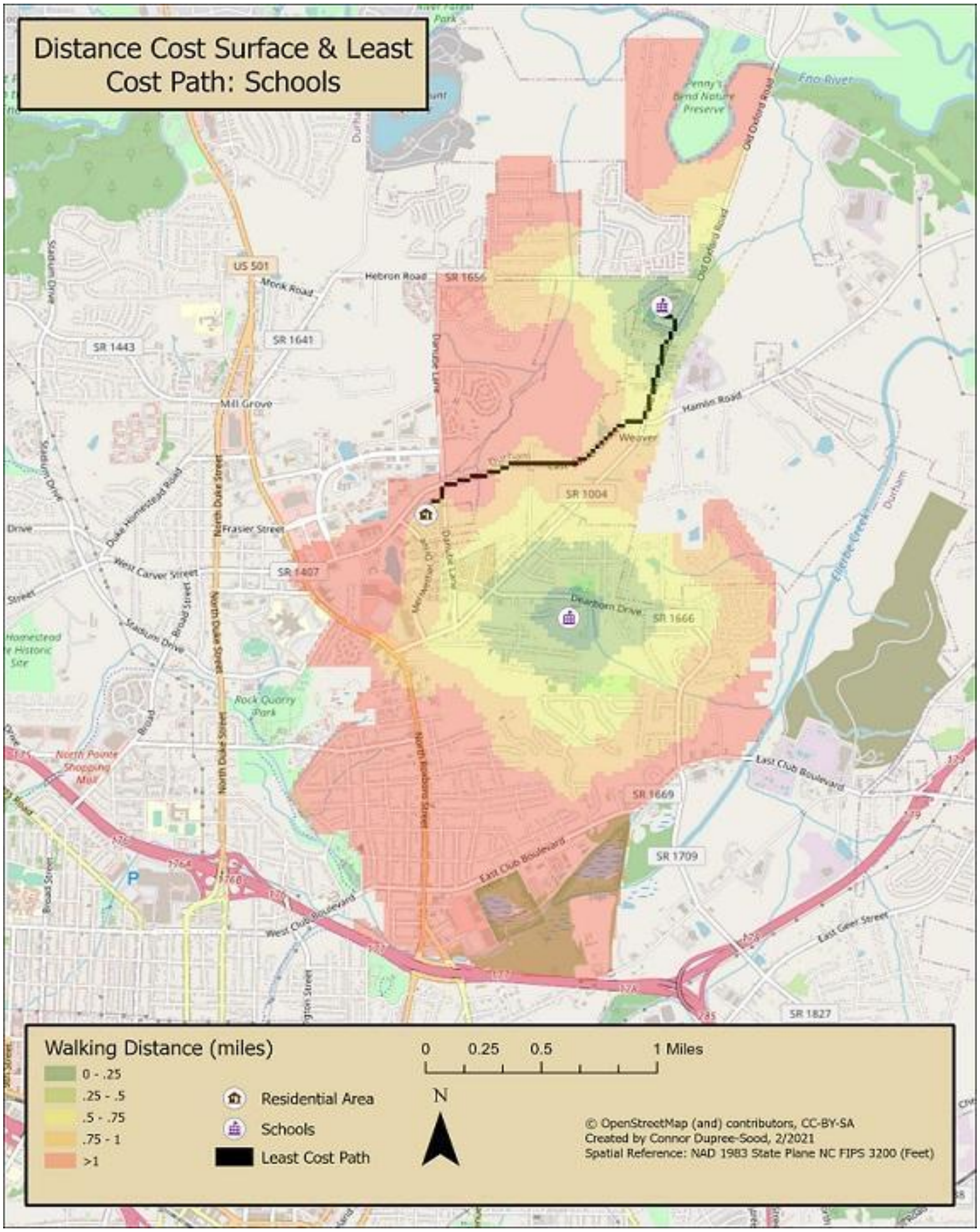

Figure 10. Example least cost path between residential areas and schools in Braggtown

This map displays the walkable areas within a mile of the two schools located within Braggtown. The pathway shows the least cost path for a resident if they were to walk to Sandy Ridge Elementary School from residential site 4.

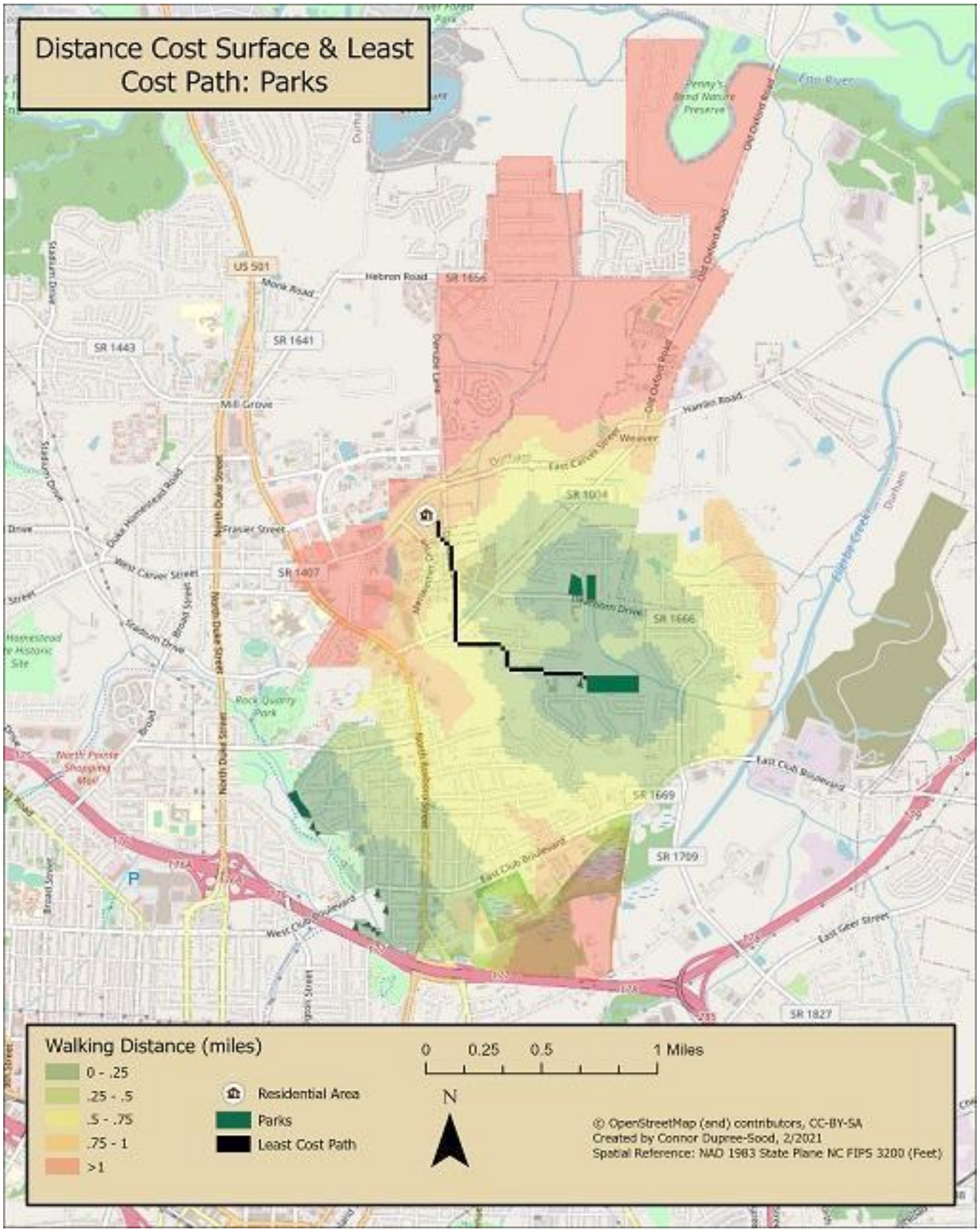

Figure 11. Example least cost path between residential areas and parks in Braggtown

This map displays the walkable areas within a mile of any one of Braggtown's parks. The pathway shows the least costly path for a resident if they were to walk to Red Maple Park from residential site 4.

Discussion

The cost surfaces and least cost paths can be helpful visuals for small area planners and those looking to enhance the connectivity of their community. They allow the viewer to gauge an area's access to features that are considered desirable walking destinations for the economic, societal, and health benefits that they may provide. These products are meant to inform the viewer on some the current walkable limitations of the examined neighborhoods, as well as display the least cost between desirable destinations. For the cost paths, the connectivity or walkability does not necessarily follow nearness relationships that are defined by Euclidean distances. Instead, this modelling approach integrates traversal costs based on currently existing infrastructure and land cover types, measuring the least cost distance from residential sites to a destination as a function of the traversal costs and distance travelled.

We intend for these products to be used in the planning phase to help guide future development. A city planner could use the maps to locate which areas lack walkable access to certain features and therefore might benefit the most from improvements, such as new walkable trails. For example, if a path shows a less costly path through a forested natural area in comparison to a longer distance along a road, then the construction of a simple foot path or trail might be recommended to enhance walkability. This would be one method for identifying ways to improve the walkability between already existing infrastructure. These paths could also be referenced during planning to identify potential locations for new commercial operations. New businesses would benefit from and add value to the paths people are already utilizing; construction along walkable corridors would result in more efficiently placed commercial areas within walkable range for more residents.

The cost surfaces created for these maps and used to form the cost path are highly dependent on the weighting assigned to the input surfaces. Weighting is designed to be adjustable based on the planner's values and objectives. Currently, the least cost path shows the most efficient using existing infrastructure; however, if the objective were to examine areas where the formation of a trail could best improve walkability, the cost weighting for forested landscapes could be lowered to encourage the path to route through existing forests. To improve understanding of the model's capabilities and limitations, the weighting of input variables and potential sources of error are discussed below.

Limitations of the Data

While the Braggtown boundary used for this case study was obtained through semi-official sources, it is not currently definitive. DataWorks worked with the local community to form an estimated boundary based on long term residents' understanding of their community edges; the boundary may not be entirely inclusive or may even include areas that some do not consider to be a part of Braggtown.

Due to the small study area, only roads, parks, and land cover types were used in creation of the cost path. The national land cover data used as an input variable for creation of the least cost path was from 2016, and no longer perfectly matched current conditions due to developmental changes in Braggtown. Inaccuracies may have resulted in least cost paths incorrectly avoiding areas that had previously been unwalkable (or routing through no longer permeable areas). To eliminate some of these discrepancies, the reclassify tool was used in combination with the raster calculator to remove roads from the land cover data. This way roads remained unobstructed by misclassified landcover pixels. The same was done to prevent land cover from designating park areas as unwalkable.

While multiple commercial zones existed within Braggtown, some were not yet in use or had very few businesses. Through an in-depth review of each commercial area, only the commercial zones that had a diverse array of goods and services were deemed relevant for this analysis. The commercial zones used are not completely representative of all non-residential facilities engaged in commerce within the Braggtown area, so some valuable businesses may have been excluded.

Limitations of the Analysis

The roads layers served as the basis for the distance cost surface, as sidewalks were identified as the main source of travel. While highways were not deemed walkable and were removed from the analysis, all other roads were assumed to be safe and walkable. All main roads and most side roads within Braggtown did have sidewalks, but the few that did not were still incorporated and considered walkable. While the original idea was to include trails and transmission lines in the walkability analysis, after clipping our study area down to just focus on Braggtown, no trails or transmission lines existed within the new boundary. Ideally both would be included in an area's walkability analysis, as they are features developers should pay close attention to when considering how to improve or make use of current walkable features.

For the creation of the least cost paths, point data was used to mark the location of the residential, commercial, and school locations. Point data represents the center of the location, so the least cost paths lead from the center of their source location to the center of the destination. While this simplification facilitated analysis, it also sometimes generated least cost paths of inflated length with incorrect endpoints (e.g., a path terminating within a building rather than at the entrance).

Finally, inaccuracies in the 2016 land cover data sometimes led to impermeable areas, such as buildings, being shown as walkable. To counteract this inconsistency all developed areas (excluding roads, which were already corrected for) were weighted to prevent permeability and avoid unwalkable pathways. As a result, cost paths avoided false positives (impermeable areas designated as walkable), but often avoided potential shortcuts between buildings or across parking lots.

VII - Conclusions and Recommendations

This project resulted in a number of separate products discussed at length in the previous sections. The cost surface products describe development suitability at a macroscopic scale, while the parcel analysis focuses the results to a scale commonly used in city planning and conservation and visualizes trends in management and development. The walkability study frames the area of Braggtown area in terms of ease of traversal and offers city planners a decision-making tool that can help inform placement of new services, businesses, and public spaces.

While these products serve different individual purposes and each provide uniquely useful information to inform decision making at their operational scales, they can also be used in tandem as a small-area planning "toolkit". To demonstrate the facility of this project at a localized scale, this section examines cost surface, parcel, and walkability products together using Braggtown as a case study. With this synthesis, we hope to exemplify how our models might be used, offer examples of the sorts of decisions these models would guide, and discuss any limits inherent to the products.

We end the section (and this report) with a list of recommendations for application of our cost surface, parcel, and walkability results.

Braggtown – Case Study

Braggtown serves as an ideal case study for comparing the results of products; it has a history of racial inequity and poverty, significant environmental assets, and a vulnerable population (see Section VI for a more comprehensive summary). Figure 12 shows Braggtown in relation to the county.

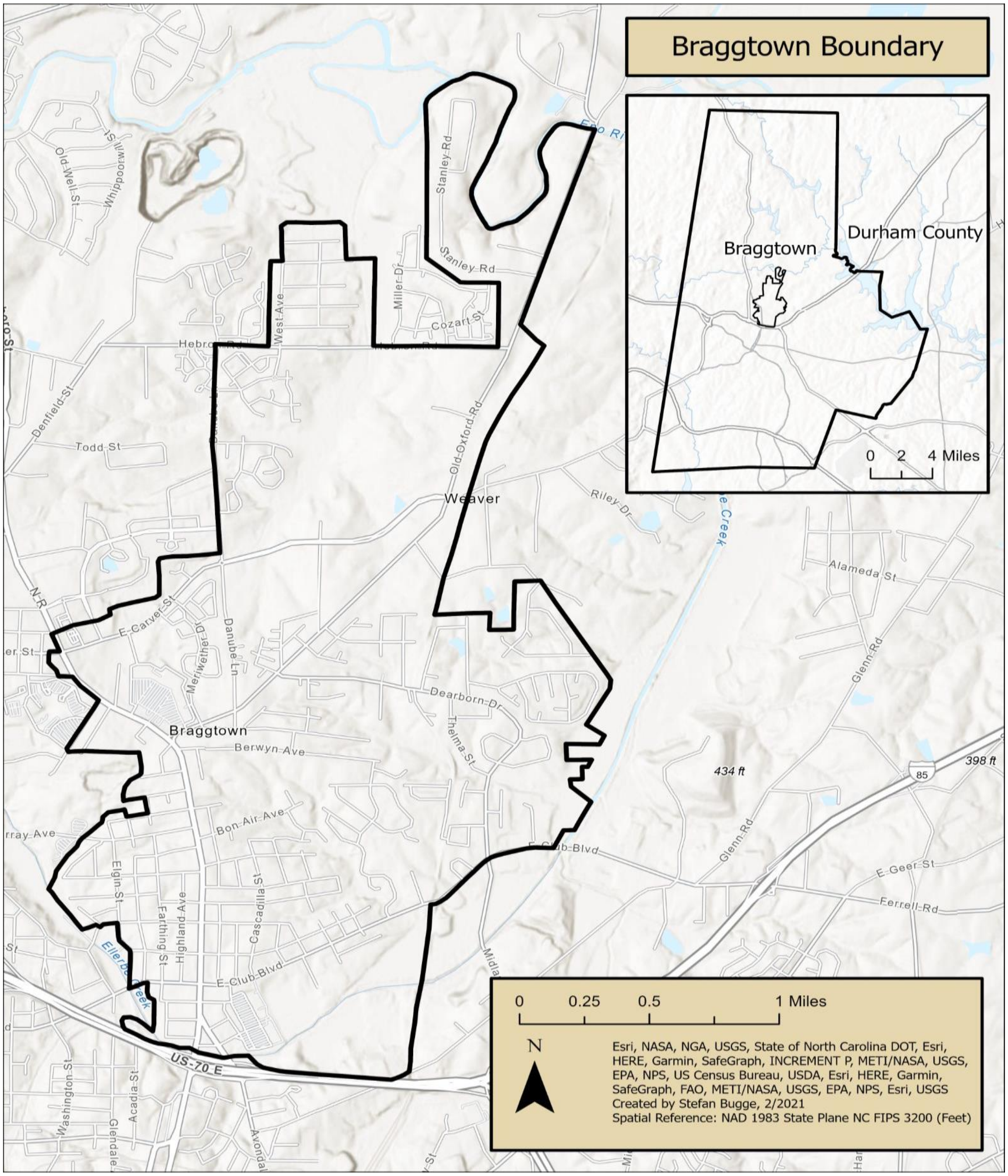

Figure 12. Braggtown in relation to Durham County

Figure 13 (next page) consists of the cost surface and parcel products for Braggtown. The cost surface offers an overall assessment of the area; development scores are higher in the southwestern and central parts of the neighborhood (where existing development is clustered) and lower in the northern and southern segments (in oranges and yellows). While the map describes areas that warrant further attention, it also lacks specific information about those areas, and areas with similar scores might have very different characteristics (a limitation of the reductive nature of a cost surface). Therefore, decision makers utilizing the cost surface might consider overlaying additional data, such as streams and roads, which could help contextualize the visuals a bit more.

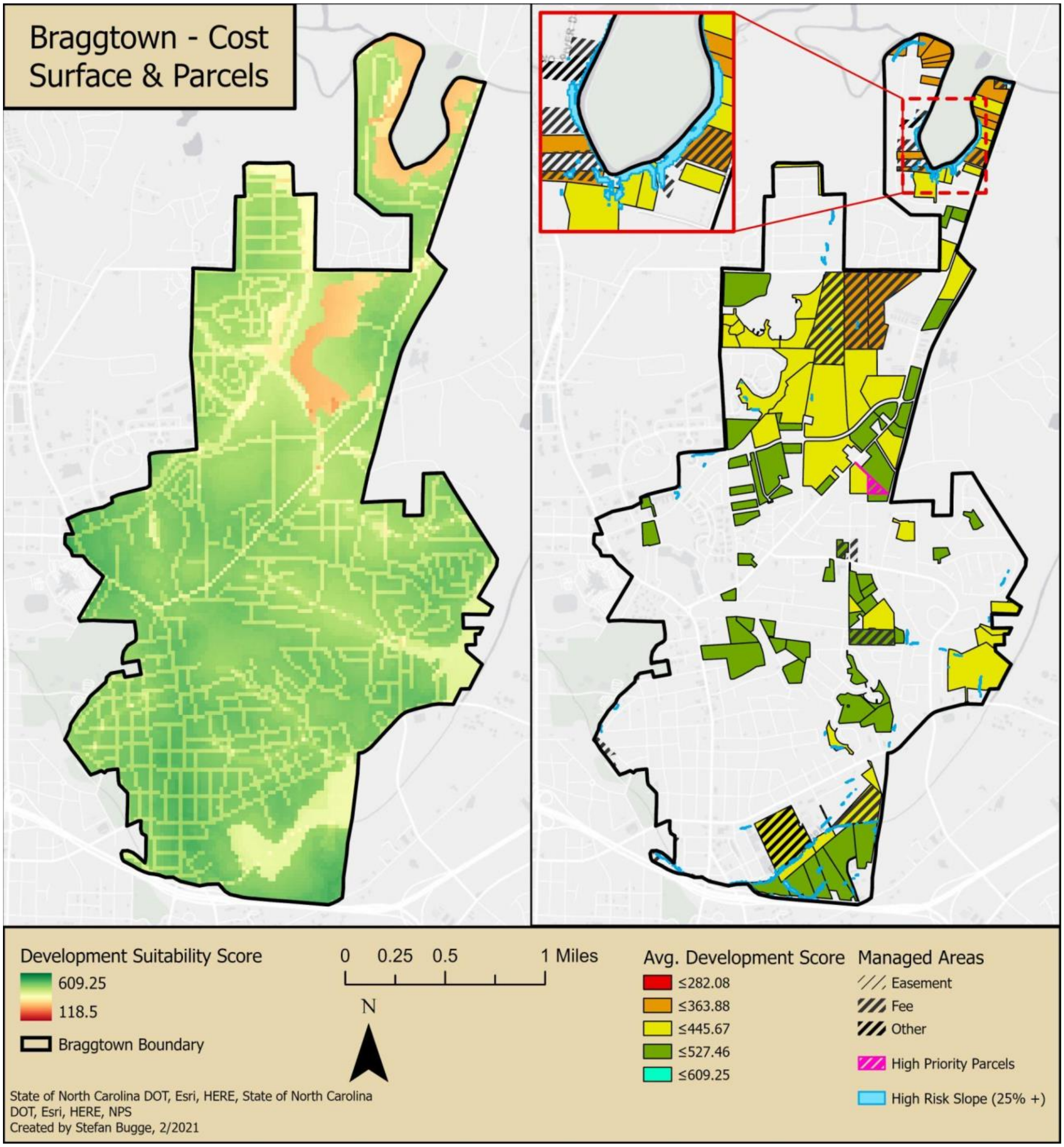

Figure 13. Cost Surface and Parcel Products Displayed at the Braggtown Level

Displaying undeveloped parcels alongside average development scores vastly improves the interpretability of products, allowing the end-user to rapidly visualize and evaluate areas of opportunity. Furthermore, managed areas and high priority overlays help exclude areas already under management or development. In Braggtown, many of the areas with conservation value have already been placed under management (notably, the Hebron Road preserve consists of three parcels in northern Braggtown, and harbors rare plant species). However, several parcels at the northern extreme of the neighborhood exhibit both low development / high conservation scores and contain flood-risk slopes; these areas are prime targets for further analysis (see zoom, figure 13). Other parcels south of the Hebron road reserve score somewhere in the middle (in yellow), but their adjacency to existing protected areas makes them attractive candidates for conservation.

On the development axis, several parcels in central Braggtown seem to be the best candidates, with higher development scores (in green) and proximity to other developed areas. These parcels should also be assessed in detail before decisions about future land use are made; as discussed in Section V, parcel products are still prone to misclassifications related to zonal application of development scores, and ground truthing should always be performed to evaluate any given site.

The lone high-priority parcel in Braggtown (bright pink) was requested for rezoning in January 2020. While rezoning requests are potential indicators of development, in this instance the parcel was requested for rezoning from county to city (an annexation), and its medium density suburban zoning did not change. This case is an example of the limitations of the high-priority layer, which is useful for tracking the frontier of development, but does not distinguish between types of rezoning or incorporate past development trends.

Examining parcel data in the context of walkability (Figure 14) further contextualizes the results, with an emphasis on designating land use based on human use and traversal. The left map shows all undeveloped parcels greater than two acres over the walkability surface, which describes the difficulty of traversing a given pixel (darker green areas are more difficult to traverse). Areas with the lowest walkability tend to line up with undeveloped parcels, which generally consist of forested terrain. The map on the right color-codes each parcel by development score.

These maps can serve as the basis for planning development along cost paths; by visualizing the most traversed route between two points alongside available, undeveloped parcels, a city planner could make informed decisions about land use. Parcels with high development scores along a least-cost path might be ideal candidates for mixed-use zoning or high-density residential zoning; forested parcels dividing commonly traversed areas from public areas such as parks might be suitable for footpaths or greenways to alter the trajectory of a given path.

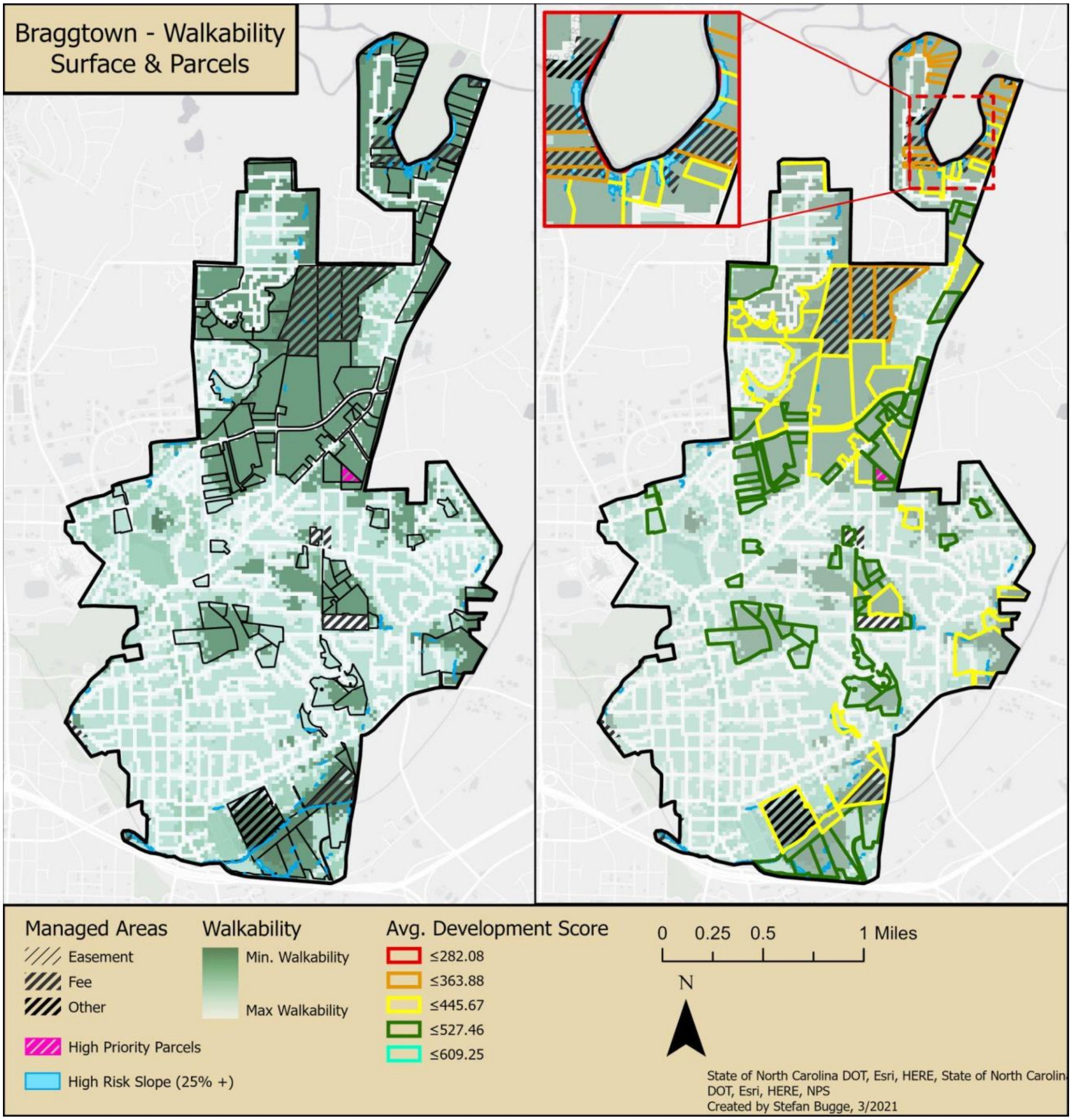

Figure 14. Parcels Overlaid with Walkability Cost Surface in Braggtown

Applied together, these products offer a "snapshot" of Braggtown for planning and prioritization. The cost surface provides a general interpretation of the study area. Examining specific parcel data offers a quick glance at undeveloped areas. Overlays, such as the managed area and flood risk layers, provide additional information to aid decision making. Finally, integrating walkability contextualizes the other layers in terms of human use and traversal and opens new avenues for comparative analysis.

Site-Specific Context

To conclude this section, we briefly examine a subset of Braggtown parcels in specific context to demonstrate how our walkability and prioritization scores might be applied in tandem at a local scale. Parcels are labeled in Figure 15 and discussed in numerical order below.

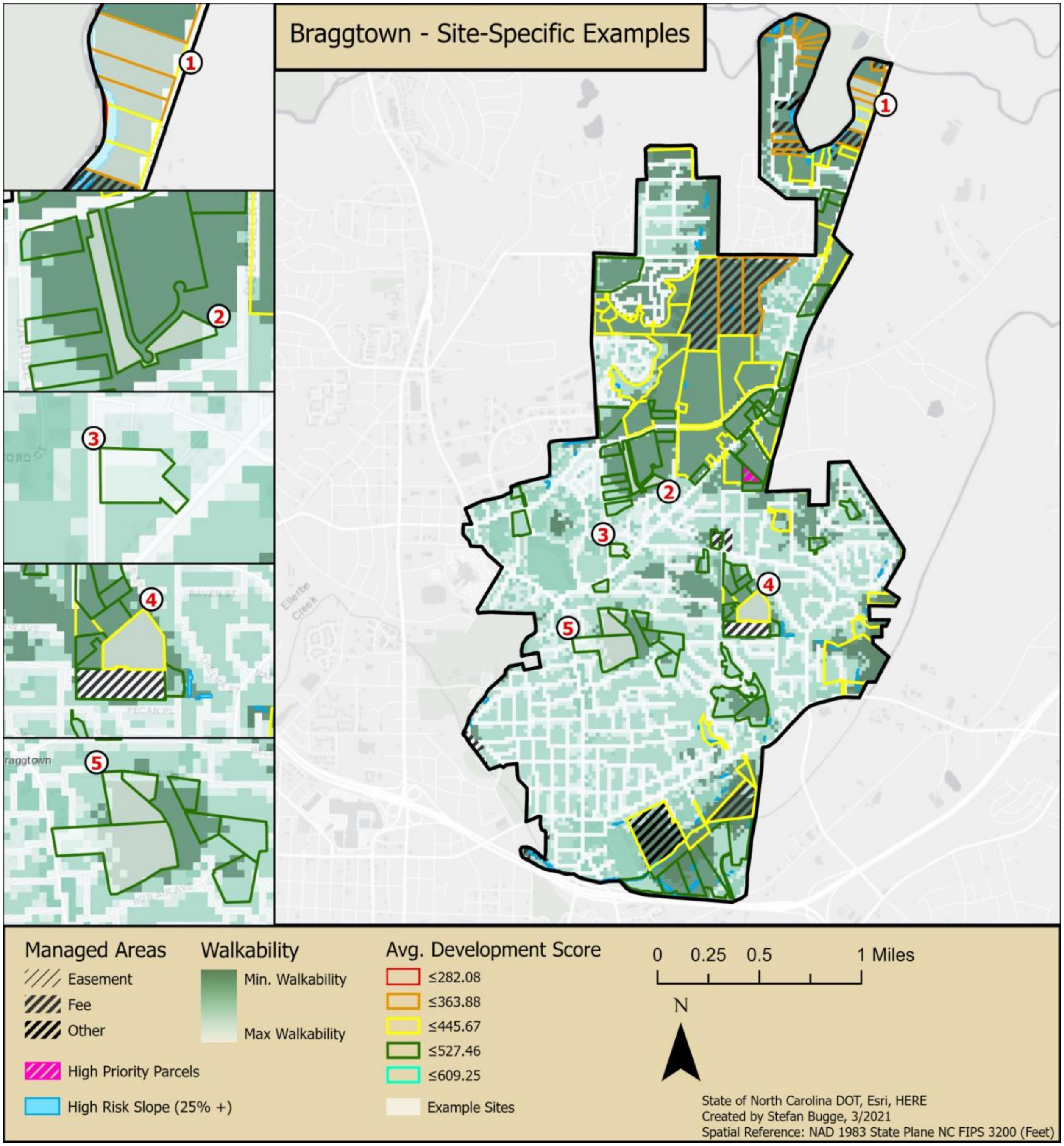

Figure 15. Site-specific Parcel Examples in Braggtown

1) These parcels represent an area of higher conservation value separate from current infrastructure. While several parcels fall within the average (yellow) development score range, portions also contain identified high risk slope areas. Conserving these parcels would prevent increases in flood risk to the FEMA designated flood zones and help create a corridor connecting two already managed areas.
2) This oddly shaped parcel exhibits a high development score value and low walkability in a central part of the neighborhood. The long thin segment of the parcel, which runs between several other high-scoring parcels, might make an ideal candidate for a trail (to preserve greenspace) or a walkable street (to amplify walkability and encourage mixed-use, nodal development).
3) This parcel is located in between multiple roads, commercial, and residential areas. Considering its low conservation value, this looks like an ideal place for future development with a focus on walkability.
4) Parcel 4 has moderate conservation value and is adjacent to a currently existing park but exhibits low walkability. Placing the land under conservation or adding it to the existing parkland would help preserve biodiversity, buffer urban heat, and extend urban habitat already present in the adjacent park. Constructing a trail through the parcel would improve walkability to the park from the residential areas to the north and provide valuable access to urban greenspace.
5) These undeveloped parcels are central and have high development scores (and low conservation value). They may be ideal areas for future development. However, some characteristics of the existing cover should be preserved to enhance walkability and retain greenspace. While the narrow gap of forest between parcels could be used for a future road, it could also be retained or converted into a trail. Because this is the only large patch of forest nearby, limiting development would buffer the urban heat island effect and help keep local temperature from intensifying. A combination of development and greenspace conservation would be ideal.

As stated before, these products should be a starting point for conservation groups or city planners - a useful heuristic for quickening the pace of prioritization. They are not authoritative, and would benefit from more comprehensive data, a more robust analytical approach in certain key areas, and a ground-truth assessment of accuracy. Nevertheless, we hope they offer utility to end users by condensing our knowledge and understanding into a set of metrics for easy application at all levels of technical understanding.

Final Recommendations

Durham is uniquely positioned as a relatively small and economically “new” city: it boasts significant acreage of natural heritage and canopy coverage and has not yet suffered the decimation of natural areas common to many urban areas. However, population growth and the accompanying rate of development threaten these resources.

Conservation of urban greenspace and smart development favoring dense, walkable environments are essential if Durham is to modernize and expand without sacrificing the city’s natural heritage. We conducted this project with these factors in mind; the following recommendations summarize how our products might best be used to prioritize conservation and development towards optimal expansion.

1. The cost surface products generated by these models offer a large-scale method to guide development and determine focal areas, but should be used with caution at local scales, as they are limited by their spatial resolution. Cost surface inputs should be updated frequently (every 2-3 years at minimum) to ensure accuracy and reliability.
2. Parcel products are a better solution for examining results at local scales (e.g., neighborhoods), and offer the most utility for selecting individual targets for conservation or development. Parcels should be researched and investigated on-site to confirm accuracy and establish specific context not included in the model. Managed area, priority area, and flood risk overlays offer additional comparative power when applied alongside parcel-level products. Parcel data, managed area data, and priority areas should be updated yearly to reflect changes in zoning and ownership.
3. Walkability analyses are most effective at smaller scales (e.g., Braggtown), and are best applied with specific sources and destinations in mind. Generation of a least cost path is the most direct way to designate focal areas related to walkability. Analyses should be sure to include areas adjacent to the study area to accurately reflect real-world patterns of movement.
4. An improved methodology for tracking current development and predicting future development would help these models better prioritize areas for conservation.
5. A full-scale analysis of the relationship between development, gentrification, and poverty would provide additional relevance to these models, especially in the context of Durham's growing population and changing demographics.

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