Desktop Recon:

Cataloguing Dry Detention Basins Using GIS and Remote Sensing

in Greenville, North Carolina

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Presented by
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Desktop Recon: Cataloguing Dry Detention Basins Using GIS and Remote Sensing in Greenville, North Carolina

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Foreword

In partial fulfillment of the M.S. Geography program at East Carolina University, this internship report documents the work performed by the author under the direct supervision of the Greenville Dry Detention Basin Project professional working team. The project is a multi-year effort to catalog and evaluate dry detention basins in the City of Greenville in order to provide support for potential retrofit proposals in the future. This report discusses the author's specific professional experience while working on the GIS-related aspects of the project. The scope of the ongoing project at-large is discussed and considered, but the methodology and results pertain specifically to the GIS application developed during the author's involvement with the project. At the end of this report, a discussion is presented on the development of the GIS, the value and anticipated future impacts of the project, the value of applied practical knowledge, and a reflection on the relevance of this work within the context of geography as a whole.

A note on GIS:

The term GIS is used many times throughout this document. GIS is an acronym for either 1) Geographic Information System, or 2) Geographic Information Science. Though these definitions are often interchangeable, this document primarily relies on the former definition—especially in any reference to GIS in the singular tense ("a GIS").

Acknowledgements

In recognition of the support and guidance I have received during my time at ECU, I would like to thank all the members of the Department of Geography, Planning, and Environment who have helped me through this program. ECU was still working through the height of the pandemic when I began work on my master's degree; I find it fair to say that we all contended with a few more road-bumps than any of us expected. I could not have made it to this point without the guidance, the understanding, and (most importantly) the patience of all the members of this department. This report is the culmination of my entire experience at ECU, from undergrad to today. In particular, I would like to thank the following:

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To Jacob, Yoo Min, and Anuradha: thank you for pushing me to prove myself.

You have all helped me learn how to be a better student, colleague, friend, and geographer.

Thank you.

Dedication

For my mom, Lorie; my dad, Brent;

my sisters, Paige, Kayce, Kelly, and Louie;

and my niblings, Markie and Duke.

Thank you for exploring this world with me.

Each of you has shaped who I am today.

I love you.

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1. Introduction

In the City of Greenville, North Carolina, much of the existing stormwater infrastructure needs to be updated. As humanity's rapid industrial growth throughout recent centuries has led to widespread environmental shifts across the globe, many coastal communities are experiencing a deficit in the capacity to cope with these changes. As climate shifts increase the frequency and severity of seasonal rainfall across North Carolina's coastal counties, stormwater management has become a severe problem for many urban communities. Design standards for stormwater infrastructure have not always anticipated the impacts of a warming climate, and many stormwater management features were not implemented with an expectation to meet the increased demand brought on by urban expansion and climate change. Additionally, many of Greenville's stormwater management features have been left uncatalogued in any official capacity. This report discusses the author's role as a graduate research assistant on the Greenville DDB Project working to address the following research question:

What are the best practices for identifying dry detention basins using remote sensing and machine learning, and how can dry detention basins be differentiated from similar stormwater control measures?

Dry detention basins (DDBs)—also referred to as dry ponds, detention ponds, etc.—are engineered depressions that have been specifically implemented for the purpose of detaining stormwater for an intermediate amount of time in order to reduce peak flow rates (Haberland et al., 2012) (**Figure 1**). Typically, DDBs are large ditches dug into the earth in areas where ground permeability has been reduced due to development. DDBs do not retain water on a permanent or long-term basis, but rather hold volumes of excess water in a central location until the surrounding environment drains out. These kinds of stormwater detention features are relatively simple to design and are easy to incorporate into development plans due to this simple nature. DDBs built by municipal agencies commonly connect to a larger stormwater management network through inlet/outlet pipes that connect to other features throughout the area. Many DDBs are built by private developers and can vary greatly in size, shape, construction material and quality, and effective placement.

Figure 1 - A Dry Detention Basin. Recent precipitation has pooled in the forebay of this DDB, located in the eastern portion of the Greenville ETJ. Image captured by the author.

Greenville has continued to develop over the last half-century, with many stormwater features having been built without being catalogued. Consequentially, Greenville has commissioned a public works project to locate, positively identify, and evaluate the many DDBs throughout city boundaries. This updated catalog of detention ponds will be incorporated into the City's stormwater management geodatabase, and the identified DDBs will be evaluated for potential retrofit. This project is being undertaken by a cooperative team of floodwater infrastructure managers and GIS professionals from the City of Greenville, with support from a cadre of environmental scientists, engineers, and data analysts from East Carolina University and the Center for Watershed Protection. The project is funded by an Environmental Enhancement Grant from the NC Department of Justice and will be carried out in phases over a duration of three years. The role discussed in this internship report will focus on the development of a Geospatial Information System (GIS) analysis methodology that will be used to remotely locate the DDBs in Greenville and record the features' locations and geospatial characteristics. The updated catalog will serve as a basis on which these basins may be evaluated and prioritized for retrofit. This process will rely on the use of LiDAR data and GIS programming to detect surface depressions throughout the City and to classify these depressions as stormwater features.

This internship report details the background, purpose, scope, vision, and planned execution of this project. My internship role has been as a research assistant on the first two project phases—geodatabase establishment and the survey/mapping of positively identified DDBs. This experience has been a practical exercise in the application of skills and knowledge I've gained throughout the entirety of my academic career, across fields including geography, GIS, cartography, and planning.

1.1. Internship Overview

I have spent the last nine months as a graduate research assistant (GRA) on a multi-organizational project team. The Greenville DDB Project ("the project") is a four-phase, multi-year study with the goal of identifying and cataloguing dry detention basins throughout the extraterritorial jurisdiction (ETJ) of Greenville, North Carolina. This internship role required twenty of hours research work per week for a total of more than 700 hours dedicated to the project. I have been specifically employed as a research assistant on the GIS application team, whose principal project goal is the development of a methodology for the remote detection of stormwater control measures (SCMs) throughout the ETJ. My regular tasks have included data interpretation, field verification analysis, subject-matter research, progress documentation, GIS programming, and the production of professional quality map products. This internship experience has provided me the opportunity to apply the situated knowledge I've gained during my time at ECU—including knowledge of geographic information systems (GIS), cartography, and urban planning—while allowing me to engage with real-world problems facing the Greenville community. My work with the project team has also allowed me to gain meaningful experience working alongside a team of subject-matter experts from multiple fields and organizations. Being a part of this project has allowed and encouraged me to expand my knowledge and expertise regarding stormwater management planning, infrastructure mapping, GIS programming, hydrologic analysis, and project management. My experience over the last year will prove to be a valuable addition to the skills and knowledge I've gained during my time at ECU.

The Greenville DDB Project has two general goals: to perform an inventory of Greenville's stormwater control measures (SCMs), and to develop a system for evaluating and prioritizing future SCM retrofit proposals. During my time on the project team, my role has included several tasks and responsibilities, but priority has been placed on one single project objective related to the first goal:

> *Perform feature detection analysis of Greenville's SCMs using LiDAR imagery. The analysis should identify nested surface depressions and provide predictions for dry detention basins. Predictions should be accurate enough to provide a verifiable list of DDBs to be included in future retrofit analysis.*

In order for the project to proceed, the tasks of identifying and cataloguing Greenville's SCMs had to be completed first. Greenville did not require registration or regular inspection and maintenance of SCM features prior to the publication of the North Carolina Stormwater Design Manual in 2017, and as stormwater management practices have evolved over the last century, specific SCM design and implementation has varied greatly. It is estimated that Greenville may have more than 300 unique SCM features throughout the ETJ, most of which are uncatalogued. The work I performed during this internship focused on the development of a GIS application that would allow the project team to perform a high-confidence prediction analysis of potential DDB features throughout Greenville's ETJ.

2. Literature Review

2.1. The Need for a Healthy Stormwater Infrastructure Network

2.1.1. **Increasing environmental flood risk factors.** As a semi-coastal community, Greenville is subject to increased flood risk brought about via climate change. Anthropogenic (human-induced) climate change is continuing to cause adverse environmental impacts around the globe. Global temperatures will likely reach 1.5°C above pre-industrial levels by 2050 (Intergovernmental Panel on Climate Change, 2018). This warming air temperature, compounded with major ice sheet loss and melting glaciers, is contributing to rising ocean levels (Meredith et al., 2019). Climate projections anticipate continuing increases in global mean sea level through the next century, with experts predicting 0.43-0.86 meters of rise by the year 2100 (Oppenheimer et al., 2019). Coastal cities in the Southeast US are particularly at risk of increased environmental impacts in a warming world. Mid-latitude storm tracks provide the majority of this region's precipitation (Hawcroft et al., 2012), with the most severe storm systems that originate in these tracks often leading to severe flooding. With increasing sea levels and rising global temperatures, these tropical storms and hurricanes have been greatly increasing in frequency and severity, with both trends expected to continue. If greenhouse gas emissions are not curtailed and mitigated, extratropical storm systems are projected to more than triple in number by the end of the century (Hawcroft et al., 2018).

In North America, as regular seasonal storm systems have increased in intensity and frequency, a proportional increase in daily precipitation intensity has been measured (Harp &

Horton, 2022). The central and east regions of the US have seen particularly acute increases in the number of days with “heavy to extreme precipitation,” with “an intensification in mean wet day precipitation between 4.5% and 5.7%” (Harp & Horton, 2022, p.4). Over the last fifty years, hurricanes and other climate disasters in the US have caused over two trillion dollars-worth of damage (National Oceanic and Atmospheric Association, 2022) and claimed thousands of lives (Insurance Information Institute, 2022). In the last decade, hurricanes and floods have displaced over 5 million US residents (International Displacement Monitoring Centre, 2022).

2.1.2. **The effects of urban growth on stormwater.** The Southeast US is home to many of the nation’s fastest-growing metropolitan areas, where rural county populations are migrating to urban centers (Census, 2017). As city centers expand outward, urban environments are regularly subjected to multiple climate change stressors and contribute to climate change in their own way. Sprawling developments become vast coverages of impermeable surfaces that generate urban heat island effects (Environmental Protection Agency, 2022a). The presence of sewer system networks combined with these impermeable areas leads to a greatly increased likelihood of local flooding (Andersen, 1970). As shifting climates push more water into coastal communities, the existing infrastructure is struggling to meet the increased demand (American Society of Civil Engineers, 2021). Much of the US’s stormwater management infrastructure was built before climate change was a design consideration; these systems simply don’t have the capacity to handle the recent increase in runoff. The materials commonly used in stormwater infrastructure have an expected rate of degradation, and many existing stormwater features are nearing the end of their lifespans. Additionally, much of the regular maintenance required to keep these features in effective operation has been lagging behind (multiple respondents, focus group interviews, February 2020).

Between the aging condition of the nation's infrastructure, the increased volume and frequency of excessive precipitation events, and the rising tides, the southeastern US is especially vulnerable to compound flood events.

In addition to increased total runoff volumes, stormwater runoff pollutant loading is acutely increased in the presence of extensive urban development (Masoner et al., 2019). As residential areas sprawl outwards, traffic becomes heavier in the area which leads to increased presence of petroleum hydrocarbons (Markiewicz et al., 2017) and heavy metals like chromium, zinc, cadmium, and lead (Hou et al., 2019). These automotive pollutants become attached to sediments on road surfaces and get carried away in surface runoff. Road runoff has been shown to contribute nearly 70% of particulate pollutants in urban pavement runoff (Ma et al., 2018). Nitrogen and phosphorous are commonly used as fertilizers in landscaping and lawncare, and these chemicals frequently infiltrate stormwater loadings after heavy precipitation events (Toor et al., 2017). Understanding the direct effects of specific contaminants is an actively evolving field of research, but it is understood that high concentrations of runoff pollution can lead to accelerated erosion of natural streams, increased eutrophication in natural water bodies, and an overall decline in water quality (Taebi & Droste, 2014).

2.1.3. **Regulation of stormwater management.** In order to understand the purpose and execution of stormwater management practices, it is important to understand the history of water quality management in the United States. In an effort to address growing concerns regarding the effects of urban growth on groundwater pollution in post-industrialized America, the Federal government has established The Clean Water Act (CWA)—one of the most significant US federal mandates that addresses the concerns of water quality. This legislation was formalized in 1978 and resulted from a series of amendments to the Federal Water Pollution Control Act of 1948. The CWA gave the newly established Environmental Protection Agency (EPA) authority to administer pollutant discharge permits by way of the National Pollutant Discharge Elimination System (NPDES). Originally, the NPDES was primarily concerned with point sources of pollution from industrial services such as manufacturing and shipping, and municipal facilities such as wastewater treatment plants. Stormwater runoff was not considered in the initial language of the CWA until the Nationwide Urban Runoff Program provided evidence that urban stormwater runoff was a significant contributor to overall pollutant levels. In 1987, amendments were made to the CWA that categorized municipal separate stormwater systems (MS4s) as point sources of pollution, and therefore these systems became subject to CWA regulations and NPDES permitting. Regulations specific to MS4s and industrial stormwater discharges were published in 1990 and amended in 1999. MS4s are distinct from combined sewer systems, in which both stormwater runoff and municipal wastewater are captured and transported through a common pipe network to a sewage treatment plant. Combined systems were frequently implemented in the latter-half of the 1800s when closed sewage systems were becoming common (Tibbetts, 2005). Most combined sewer systems still in use today are located in the Northeast and Pacific Northwest (EPA, 2022b). In a combined system, pipes are generally wider in diameter in order to accommodate the greater total volume, but in times of excessive and sudden precipitation even these wider pipe networks (or even the sewage treatment plant itself) can become overburdened by the increase in demand. In a worst-case scenario, an overburdened combined sewer network can result in a combined sewer overflow, where the mixture of surface runoff and toxic sewage is forced out back of the system. Discussion is ongoing within the municipal planning community as to whether a combined system is preferable over an MS4, but the majority of US cities operate their stormwater systems separately from municipal wastewater.

The City of Greenville operates its stormwater management network separately from its municipal wastewater system (North Carolina Department of Environmental Quality, 2018b), and is therefore subject to MS4 permitting under the NPDES program. The City currently maintains a Phase II permit, which is applicable to MS4s that serve urban areas with fewer than 100,000 residents. However, Greenville has shown a consistent growth rate over the past, and may require a Phase I permit (for urban areas over 100,000 residents) in the future. In the state of North Carolina, the Department of Environmental Quality (NCDEQ) administers permits for CWA MS4 permits, as well as permits for the state's Stormwater Permitting Program (SPP). As per the NCDEQ, the SPP "develops, plans and implements statewide stormwater control policies, strategies and rules to protect surface waters of North Carolina from the impacts of stormwater pollutants and runoff." (NCDEQ, n.d., n.p.). NCDEQ has published and codified the technical mandates regarding stormwater management in the Stormwater Design Manual (SDM).

Because water quality management has not always included guidance on stormwater management, stormwater management features have not always been developed according to a uniform design standard. Specific stormwater infrastructure design has often been derived from common construction standards (ASCE, 2021). What has often been seen as the responsibility of civil engineers has become a much larger issue that requires combined input and consideration from engineers, urban planners, municipal administration, and community members. Most of the rapidly expanding metropolitan areas in the southeast are incorporating more robust stormwater management techniques as they continue to grow, but many more jurisdictions—including Greenville—are facing the task of upgrading or replacing their existing stormwater infrastructure.

2.2. SCMs and their purpose.

There are many considerations involved in urban stormwater management, from conceptual perspectives like land-use planning to practical approaches like infrastructure engineering. This report regards the specific implementation of physical stormwater management features that address the flow and filtration of stormwater runoff: SCMs. Within the area of stormwater management, SCMs are engineered physical developments that are designed to manage stormwater runoff for both peak flow volumes and pollutant transport. As per NCDEQ mandate (in accordance with NPDES), high density developments are required to address stormwater runoff impacts that result from the construction of impervious surfaces such as pavement and rooftops (NCDEQ, 2017a). This can be done in two ways: by "runoff treatment" where suspended pollutants are filtered out via SCMs, or by "runoff volume match" where overall area development is done in such a way as to preserve local hydrology by using practices and strategies that promote infiltration and/or evapo-transpiration of stormwater runoff volumes. Runoff volume match is intended to create developments where hydrological disruptions that result from development are minimized.

Runoff treatment is the main purpose of SCMs, alongside flood risk mitigation. SCMs are categorized as either primary or secondary, based on their ability to reduce a given concentration of pollutants from a given volume of surface runoff. In general, Primary SCMs are expected to remove at least 75% of total suspended solids (TSS) in a test scenario (100 mg/L suspended in 1.5 inches of runoff) (NCDEQ, 2018a). Secondary SCMs are those that do not meet the filtration criteria of a Primary SCM. Despite this division between SCM classes, many structural and design aspects are common across all SCM features. The SDM defines 16 minimum design criteria (MDC) common to all SCMs, which address placement, purpose, and implementation. Many of the general MDC do not directly prescribe the physical design of a given SCM, but there are four MDC from which the GIS team has gathered insight regarding the spatial aspects of any given feature. Consider the following general MDC directives from SDM section C-0 (NCDEQ, 2017b):

- General MDC 1: Sizing. *"The design volume of SCMs shall take into account the runoff at build out from all surfaces draining to the system. Drainage from off-site areas may be bypassed. The combined design volume of all SCMs on the project shall be sufficient to handle the required storm depth."*

From this guidance, it can be assumed that an SCM will have a certain ratio of volume-to-catchment-area. This ratio can be calculated and analyzed if the catchment area of a particular depression stack can be accurately estimated.

- General MDC 2: Contaminated soils. *"SCMs that allow stormwater to infiltrate shall not be located on or in areas with contaminated soils."*

From this guidance, it can be expected that any properly implemented SCM will not be located over a contaminated soil site, such as a brownfield.

- General MDC 3: Side slopes. *"Side slopes of SCMs stabilized with vegetated cover shall be no steeper than 3:1 (horizontal to vertical)."*

From this guidance, it can be assumed that any depression with a side slope ratio steeper than 3:1 will not likely be an SCM (though this MDC does allow for certain exceptions).

- General MDC 8: Maintenance access. *"Every SCM installed pursuant to this Section shall be made accessible for maintenance and repair. Maintenance accesses shall: (a) have a* *minimum width of ten feet; (b) not include lateral or incline slopes that exceed 3:1 (horizontal to vertical); and (c) extend to the nearest public right-of-way."*

- General MDC 9: Easements. *"All SCMs and associated maintenance accesses on privately owned land except for those located on single family residential lots shall be located in permanent recorded easements."* Additionally, *"The entire footprint of the SCM system must be included in the access and maintenance easement, plus an additional ten or more feet around the SCM to provide enough room to complete maintenance tasks."*

From General MDC 8 and 9, it can be expected that an engineered SCM will have a clearance of at least 10 feet in a buffer around the main pool or channel.

It can also be helpful to understand typical structures associated with various types of SCMs. Bioretention cells (**Figure 2a**) are relatively small, excavated areas filled with particular soils and vegetation intended for filtration, and have an underdrain with cleanout pipes and a single inlet (NCDEQ, 2020a). These kinds of SCMs typically exhibit similar basic design structure as DDBs, with the primary difference being in soil composition. This is one example of why field verifications are crucial to the identification process. Stormwater wetlands (**Figure 2b**) are typically large areas near the local water table that mimic the function of natural wetlands. These features tend to have shallow pools and thick vegetation (NCDEQ, 2020b). If a DDB is left unmaintained for an extended period of time, it may naturally develop into a wetland. Treatment swales (**Figure 2c**) are a type of secondary SCM that slow peak runoff rates and often include check-dams that obstruct the flow of debris and sediment; these kinds of SCMs are long, wide, and shallow, with a trapezoidal cross-section (NCDEQ, 2020c). From a remote sensing perspective, these kinds of features may appear similar to a very long DDB.

Figure 2 - Common SCMs. From top to bottom: a) a bioretention cell, b) a stormwater wetland, and c) a treatment swale. Images source: Stormwater Design Manual, NCDEQ, 2020.

2.3. Technical specifications of DDBs.

Dry detention basins are a form of secondary SCM. The primary purpose of DDBs is to attenuate peak stormwater runoff rates; they typically have very little capacity for pollutant removal, if any. However, DDBs are frequently implemented in conjunction with a primary SCM further along the network; DDBs enable a connected primary SCM to maintain its pollutant removal effectiveness without becoming overfilled during times of heavy precipitation. DDBs provide a large catchment volume for the surrounding area, where excess runoff can be drained down over 2-5 days.

Per the SDM, a properly implemented DDB should be designed with the following features (**Figure 3** and **Figure 4**): a temporary pool in which the detained runoff volume will be held, an inlet structure, an outlet structure, uniform grading of the bottom of the basin, vegetated side slopes, and an emergency spillway (NCDEQ, 2020d). Any given DDB will be designed with particular considerations for the required volume to be detained and considerations for the local geography. Each DDB is expected to be designed with similarities in overall dimension and shape, but it is understood that real-world examples will likely be unique in layout and dimension.

Greenville's Stormwater Management Department estimates there to be 300 or more DDBs throughout the city, the majority of which are uncatalogued. The GIS application will therefore need to be able to identify *and* classify nested surface depressions detected in the DEM. Crucially, the technical specifications provided by the SDM regarding DDBs were only made official in 2020, and the SDM itself wasn't published until 2017. Runoff treatment mandates have been in place in Greenville since 2004, but these do not regulate physical design structure. Stormwater management principles have historically encouraged developers to design SCMs

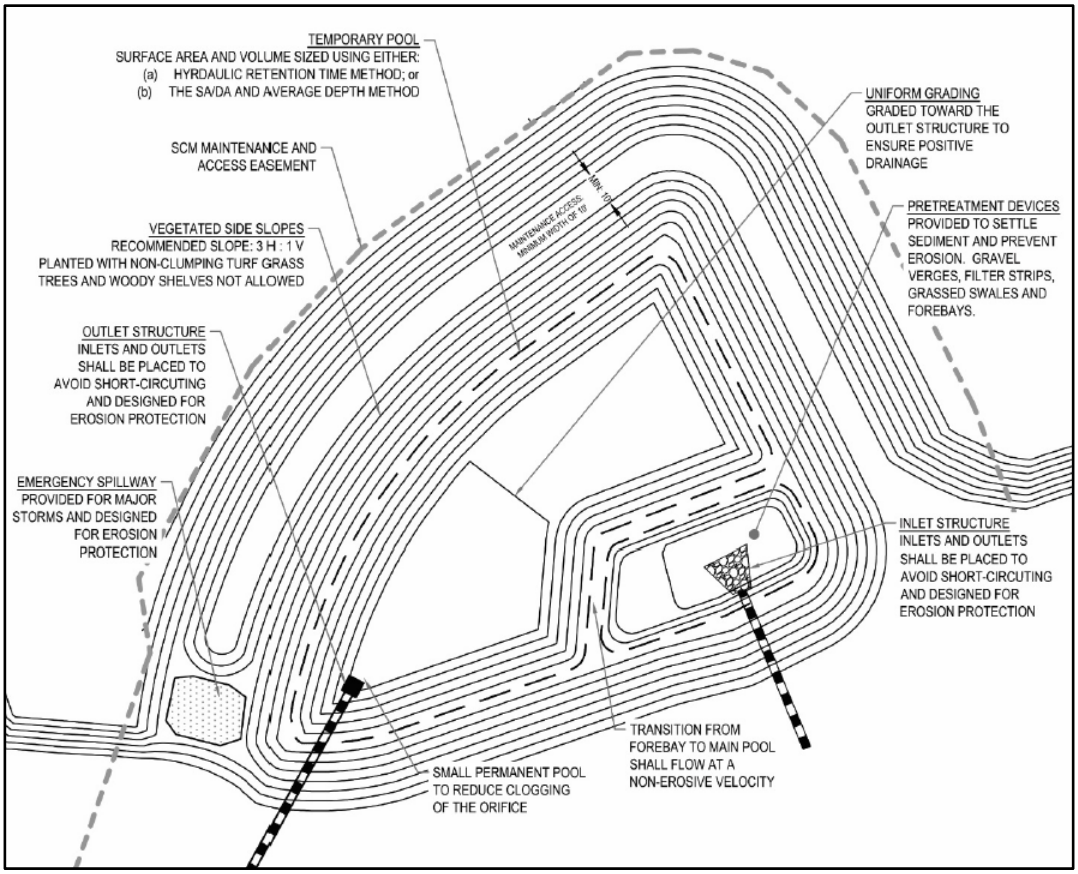

Figure 4 - Dry pond example: plan view. Underlined indicators identify specific minimum design criteria. Figure source: Stormwater Design Manual, NCDEQ, 2020.

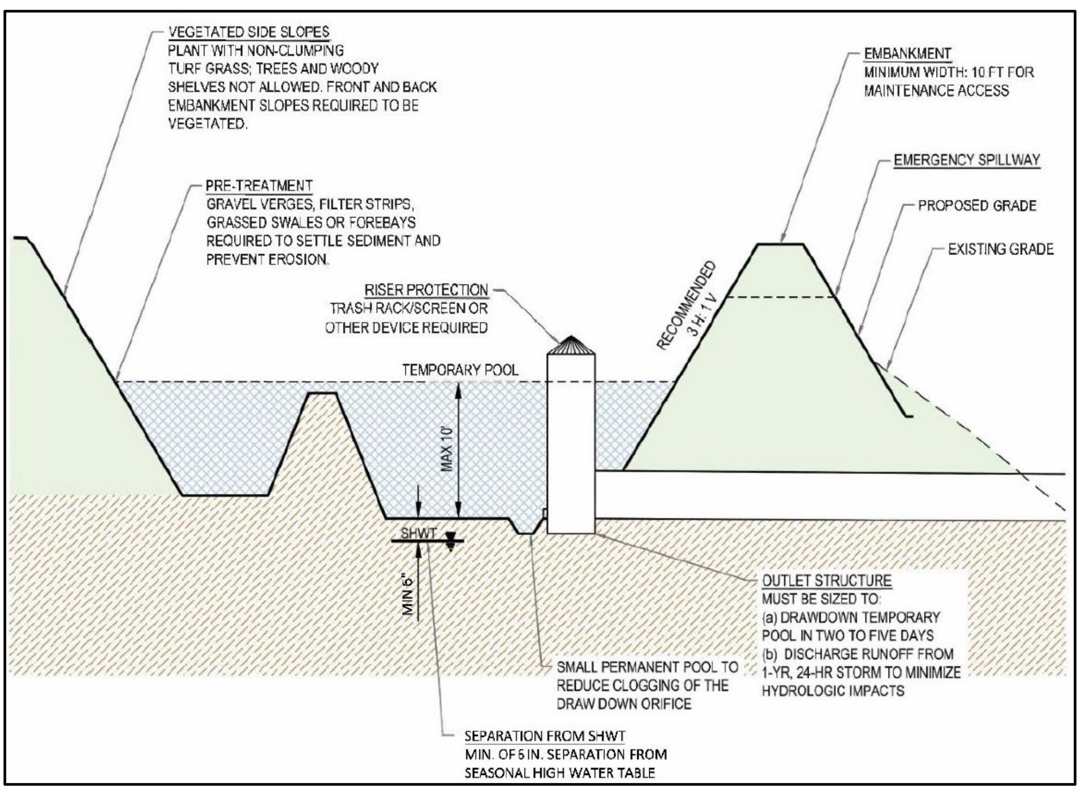

Figure 3 – Dry pond example: cross-section. Figure source: Stormwater Design Manual, NCDEQ, 2020.

according to the best management practices of the time, so the design structure of a given DDB may be significantly different from other DDBs built at a different time.

2.3.1. **Tracking favorable conditions for retrofit.** As part of the long-term objectives of the project, it will be useful for the GIS to capture attributes of candidate DDBs that can be useful in evaluating them for retrofit priority. Helpful characteristics may include some of those that are being used by the GIS to predict DDBs (such as volume and area), but some additional characteristics may be worth calculating during the identification process, though they won't necessarily contribute to the identification process itself. An example of this is parcel ownership; retrofitting DDBs on privately owned parcels would require permissions from the owning party, whereas a DDB on municipal land needs no additional permissions. Including these sorts of non-identifier attributes is useful for the overarching objectives of the project.

2.4. **Similar applications of remote sensing.**

Raster-based **s**urface depression detection is the critical first step of the planned analysis. Hydrologic modelling often relies on depressionless DEMs to conduct watershed modelling (Tahmasebi et al., 2017), so environmental engineers and hydrologists frequently rely on GIS tools to identify and delineate surface depressions in order to perform this analysis (Wu et al., 2019; Islam, 2020; Mhina et al., 2021). In the early 2000s, a case study utilized bare-earth LiDAR DEMs to identify detention basins through the Houston metropolitan area of Texas (Wang & Liu, 2006; Liu & Wang, 2007). This was a novel approach for its time, establishing the use of a least-cost search algorithm on the raster layer. Each cell is calculated for its spill elevation and optimal flow path, which results in the simultaneous cataloguing of delineated nested depressions, optimal flow path networks, and watershed boundaries. Common methodologies prior to this study required excessive processing times to analyze the high-resolution LiDAR DEMs that had become more recently available. Because the method proposed by Wang & Liu (2006) utilized object-oriented programming languages (C++ and Java), the multiple-step process that had been common for depressionless DEM generation could now be done in a single execution; this radically reduced the overall processing requirements. This particular case study serves as the proof-of-concept for the planned approach to the GIS objectives of the DDB Project. This methodological approach to surface depression modelling is still greatly favored, and forms the basis of many pre-packaged geoprocessing tools today.

Surface depression detection has also been used in exploratory feature mapping. In one example, a report concerning the delineation of karst doline structures in Mexico describes a successful application of geomorphic mapping using LiDAR DEM data (Moreno-Gómez et al., 2019). Karst is a subterranean area where the long-term dissolution of carbonate rocks by the natural water table has resulted in extensive subsurface networks of caves and conduits (Moreno-Gómez et al., 2019, p.1); dolines are the naturally occurring sinkholes that open on the surface of this kind of terrain. Mapping dolines helps hydrologists understand the substructure of the karst terrain, as dolines serve as catchment areas for localized precipitation and feed runoff directly into the water table. In this report, the authors rely on a fill-difference algorithm to raise elevation cells and then sort them into a binary classification of depressions. This process is similar to the previously mentioned Wang-Liu method, albeit without the flow analysis. The difficulty in mapping karst dolines, however, is that often times individual dolines lay within larger depressions; this means that a simple overall delineation of depressions will not result in an appropriate delineation of dolines. Previous attempts to avoid this problem generally relied on establishing a depth threshold that had to be fit to the particular area being studied, which could result in the algorithm neglecting dolines below that threshold. To avoid these kinds of omissions, Moreno-Gomez et al. create vectorized contour slices at variable depths within the detected depressions, which results in a nested depression hierarchy. With an established hierarchy, individual dolines within a larger depression could be accurately mapped. This is the crucial part of the doline mapping approach, and this provides inspiration for the DDB mapping approach. By generating nested depression contour stacks, the GIS team will be able to delineate actual engineered DDBs from otherwise naturally occurring depressions or low areas.

Most of the similar GIS-based efforts in the literature catalog regard the identification and delineation of depressions from a LiDAR DEM, which informs the GIS team that the project goal is certainly attainable. However, none of these efforts explore the challenge of differentiating between multiple depressions with similar shape metrics. This part of the identification process is the unique focus of the GIS team's efforts on the Greenville DDB Project.

3. The Greenville DDB Project

3.1. Project Conception

3.1.1. **Opportunity: The EEG Program.** The North Carolina Department of Justice administers the state's Environmental Enhancement (EEG) Program, which offers reimbursement grants for projects that improve North Carolina's air, water, and land quality. Grants are available to non-profit organizations, government agencies, and educational institutions for projects regarding (among other things) restoration, remediation, research, and education. Previous projects have addressed land restoration, stormwater remediation, stream stabilization, and the impacts of industrial livestock farming. The funding for the EEG program results from the Smithfield Agreement—an accord made in 2000 between the NC Attorney General and one of the state's largest industrial livestock companies, Smithfield Foods. Per the 25-year agreement, Smithfield Foods provides $2 million per year for environmental projects throughout the state. Awards are administered by the NC Attorney General and range from $5,000 to $500,000 for three-year projects. Project proposals are favored for including factors regarding overburdened and underserved communities. At time of writing, the EEG Program has disbursed more than $41 million across 210 projects (NCDOJ, 2023).

In 2021, the NCDOJ Attorney General's Office awarded $149,241 to ECU for a project to address Greenville's stormwater infrastructure. The project proposal was composed by ECU faculty and staff members Mike O'Driscoll, Guy Iverson, and Rob Howard, as well as Lisa Fraley-McNeal and Bill Hodgins from the Center for Watershed Protection (CWP). In summary, the project was proposed as a multi-year research project to "address some of the [Greenville's] stormwater challenges … by mapping and evaluating dry detention basins around the city and identifying those that pose a risk to water quality and flooding" (O'Driscoll et al., 2019). Included in the proposed project budget was an allotment for funding research assistant positions at the graduate and undergraduate level.

3.1.2. **Benefit: stormwater management for flood risk reduction.** Greenville has an extensive history of flooding. The City has weathered multiple catastrophic hurricanes in the past—including Hazel in 1954, Floyd in 1999, and Florence in 2018—in addition to irregular riverine flooding from excessive precipitation in the area. Greenville sits at a base elevation of 56ft (USGS, 2000), with its terrain gently sloping downward toward the Tar River, which bisects the city through the middle. The City has mapped over 10,000 acres of floodplains (Greenville Engineering Department, *n.d.*) within its 39,565-acre jurisdiction (City of Greenville, 2018), meaning a full quarter of the City's territory lies within a floodplain (1% annual flood chance). The large majority of this floodplain area lies parallel to the Tar River running from west to east through the middle of the area. Much of the terrain is made up of swampy lowlands and marshes; during regular rain events, these areas soak up excess runoff like a sponge and store that water until it can be absorbed into the water table. As the city has grown, engineered features have been built and incorporated into a city-wide stormwater control network in order to offset the expansion of impervious surfaces across the area. Since the 1970s, the City has required peak stormwater runoff controls to be emplaced in order to offset the growing extent of impervious surfaces that accompany said development. These peak runoff controls, or SCMs, take many forms including bioretention cells, treatment swales, stormwater wetlands, and dry detention basins.

Understanding Greenville's Compound Flood Risks

Seasonal precipitation trends in the southeast US have been increasing in both frequency and severity over recent decades. Greenville's geography puts it at particular susceptibility for multiple flood risk factors which add to and compound one another. DDBs exist as only one class of features within the wider stormwater control network, and rapid concentration of high-precipitation storm events can (and do) overload the network at-large. Essentially one-third of North Carolina lies in the Coastal Plain, and shallow water tables can easily be saturated by multiple heavy downpours in quick succession. Storm events don't need to be in direct proximity of each other in order to create compound flood risks. Tropical storms create particularly hazardous scenarios: the storm will approach the Carolina coast and push water upriver while dropping continuous and heavy precipitation much further inland. If there has been another heavy precipitation event in the region within a recent timeframe, the regional water table will already be at or near capacity. The additional precipitation of the oncoming storm cannot be absorbed, and the area will face a combination of fluvial, pluvial, and coastal flood risks. Inland rains can cause riverine flooding, the approaching storm cell can create coastal flooding, and all the excess surface runoff in between will create flash flooding. Hurricane Floyd in 1999 was one particular example of a compound flooding scenario, as Hurricane Dennis had swept through the area two weeks prior and left the water table saturated on Floyd's arrival.

Source: Curtis et al., 2021.

Specific SCM design has historically been left up to the developer, so long as they abide by the best available practices at time of implementation. Because of this, SCMs have varied greatly in execution throughout the past. Prior to the early 2000s when stormwater management practices began placing more importance on the implementation of green stormwater infrastructure, DDBs were the most common SCM of choice for new development in Greenville. DDBs are less complex than other SCMs and easier to implement because they prioritize peak runoff control at the cost of having very little impacts on runoff filtration. The City of Greenville estimates there to be several hundred SCMs throughout the ETJ, most of which are expected to be DDBs. Greenville established nutrient management requirements for new SCMs in 2004, but it wasn't until NCDEQ published the Stormwater Design Manual in 2017 that Greenville began requiring registration and regular inspection & maintenance of the city's SCMs (O'Driscoll et al., 2019). Because of this, there are only approximately 30 SCMs that have been registered in the City's stormwater database; the rest of Greenville's SCMs are uncatalogued and in need of inspection. Without regular maintenance, DDBs have the potential to become clogged with sediment buildup, trash, and debris, which can reduce their effectiveness or eliminate it altogether.

3.1.3. **Benefit: retrofitting for stormwater filtration.** The North Carolina Stormwater Design Manual strongly encourages the exploration of SCM retrofit opportunities and recommends prioritizing retrofit opportunities over implementing new SCMs. Retrofits can be made to any area that currently lacks or has inefficient nutrient and/or sediment loading. Existing SCMs make for ideal retrofit candidates as new land acquisition is not always possible, the initial engineering will have already been performed, and retrofits can be undertaken at the same time as any currently required maintenance or concurrent site construction/modification. The Stormwater Design

Manual encourages creativity in consideration of retrofit approaches; improvements can be as simple as expanding the existing catchment area, or draining a new impervious surface layer into an existing SCM that can accept the additional capacity. In the same way that the specific SCM design is informed by the surrounding geography, potential retrofit designs are informed by the existing SCM (or lack thereof).

DDBs in particular make for prime retrofit candidates due to their typical lack of filtration capacity, and their flexibility of use. One of the most common retrofit approaches is to convert an existing DDB into a stormwater wetland. By planting particular filtration-adept vegetation to the basin and implementing a forebay around the outlet structure, stormwater can pool in the bottom of the basin as the plants filter out pollutants. Other retrofit approaches include widening or deepening the existing basin to provide a larger detention volume, emplacing an underdrain, or replacing the basin's soil with sand and particulate to create a sand filter. Not all retrofits necessarily need to address filtration, either. Adding a trash rack over the outlet will help reduce the flow of large debris, for example.

3.2. Goals of the Greenville DDB Project

The Greenville DDB Project is intended to address two connected needs of the city. Firstly, Greenville's existing SCMs need to be catalogued; the city needs an updated record of its stormwater network, if for no other reason than to have a more complete stormwater geodatabase. Secondly, there is a need for the city's SCMs to be evaluated for functionality and condition. It is important to continuously maintain and improve the city's stormwater network so as to mitigate local flood risks as much as possible, and to increase the filtration of stormwater runoff.

As proposed in the EEG funding proposal, the Greenville DDB Project has outlined the following objectives:

- Collaboratively develop a geographic information system (GIS)-based geodatabase that can document all stormwater control measures in the City.
- Gather and evaluate existing (previously collected) data for stormwater control measures in Greenville.
- Design and implement a field, remote sensing, and GIS-based program to map the stormwater control measures that are not currently accounted for.
- Utilize site visits and pre-existing data to evaluate the status of dry detention basins in Greenville (not currently inspected or mapped).
- Evaluate the dry detention basins across the City and develop a prioritization system for retrofit sites, with an emphasis on those located in underserved neighborhoods.
- Develop a list of sites where retrofits are feasible, with an emphasis on those in underserved neighborhoods.

- Engage property owners and students to understand the stormwater impacts and potential improvements associated with retrofits.
- Develop proposals to seek funding to implement retrofits for dry detention basins in underserved communities.

This internship focuses on the first four of these objectives. Taken as an entire effort, the overarching goal of the Greenville DDB Project is to catalog the city's dry detention basins in order to provide analytical support for future retrofit proposals that will help mitigate flood risk and improve stormwater runoff filtration in the area, especially in or near underserved communities.

3.3. **Project Execution**

The Greenville DDB Project will have a planned duration of three years (see **Appendix 3**), from January 2022 through December 2024. The project officially began in Q1 of 2022 and, at time of writing, is nearing the midpoint of its anticipated duration. The project will be loosely broken into four phases (**Figure 5**), with each containing multiple project objectives (PO):

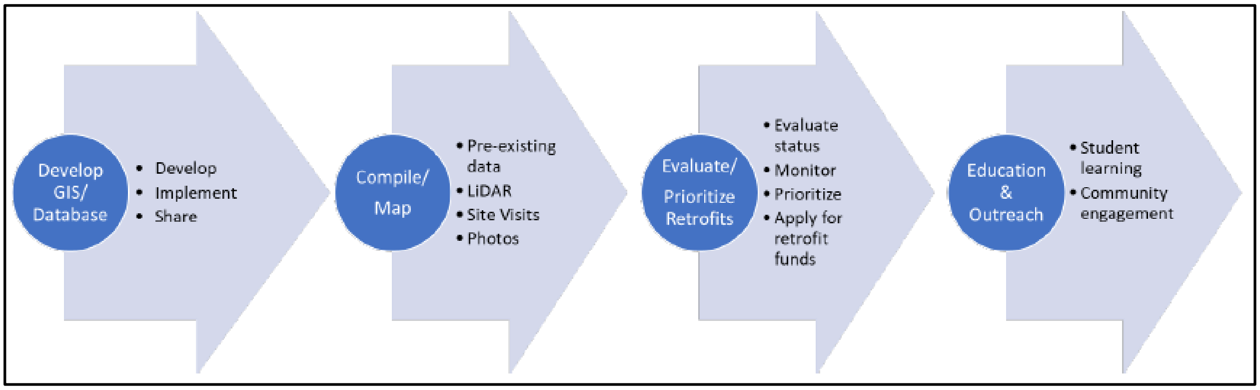

Figure 8 - Greenville DDB Project Phases. Phase 1: GIS & Database Development; Phase 2: Compile & Map the City's DDBs; Phase 3: Evaluate & Prioritize Retrofits; Phase 4: Education & Outreach. Figured cited from O'Driscoll et al., 2019.

- Phase 1: GIS & Geodatabase Development
  - PO: <u>Develop</u> a geodatabase for cataloguing Greenville's SCMs
  - PO: <u>Implement</u> a GIS approach for identifying unmapped SCMs
  - PO: <u>Share</u> findings with the city (and GIS with others, if possible)
- Phase 2: Compile and Map Greenville's DDBs
  - PO: Utilize <u>pre-existing stormwater data</u>
  - PO: Incorporate existing <u>LiDAR</u> DEMs
  - PO: Perform <u>site visits</u> to verify the GIS predictions
  - PO: Collect preliminary data and <u>photos</u> for evaluation

- Phase 3: Evaluate and Prioritize Retrofits
    - PO: Evaluate the status of Greenville's SCMs
    - PO: Monitor retrofit candidates for filtration effectiveness
    - PO: Prioritize candidates for retrofit proposals
    - PO: Apply for retrofit funding
- Phase 4: Education & Outreach
    - PO: Incorporate and foster student learning opportunities
    - PO: Participate in community engagement efforts and collect input

The GIS work performed throughout this internship makes up the first two phases. These project phases are "loosely" segregated because POs from separate phases may be addressed concurrently, while other POs may require the completion of prior POs before being able to begin. Because of this, there is an understandable level of overlap between the project phases, though it is anticipated that they will be completed in a linear order. At the time of writing, Phase 1 has been completed, Phase 2 is nearly complete, and Phases 3 and 4 are underway.

3.4. Internship Role and Expectations

My role is as a graduate research assistant (GRA) working under the direct supervision of Mr. Rob Howard. As a member of the GIS compartment of the project team, GRA duties involve the following:

- Assist Mr. Howard in the development of the GIS, including script testing, conceptual design, and keeping a record of changes.
- Perform field validations for the improvement of GIS predictions.
- Participate in principal field surveys of prime DDB candidate sites.
- Perform research on the nature of SCM design and Greenville’s stormwater history.
- Generate professional-quality map products reflecting the project’s progress.
- Engage in opportunities to spread awareness of the project and advocate for the team.

This list is not exhaustive; other duties may be assigned according to the immediate need of the project at large. It is expected that the GRA will engage actively with the requirements and objectives of the project, and will explore opportunities to advance the team’s progress. The GRA should prioritize the GIS portions of the project before seeking to address objectives delegated to other project team compartments. It is worth noting that while Mr. Howard is my direct supervisor, the ultimate hiring authority and delegation of project responsibility lies with the project administrator, Dr. Mike O’Driscoll. Internship duties began August 16, 2022, and will extend through May 4, 2023. Obligations relating to the GRA position are ongoing, and not all tasks or duties will be addressed in this report.

4. Methodology

4.1. Study Area

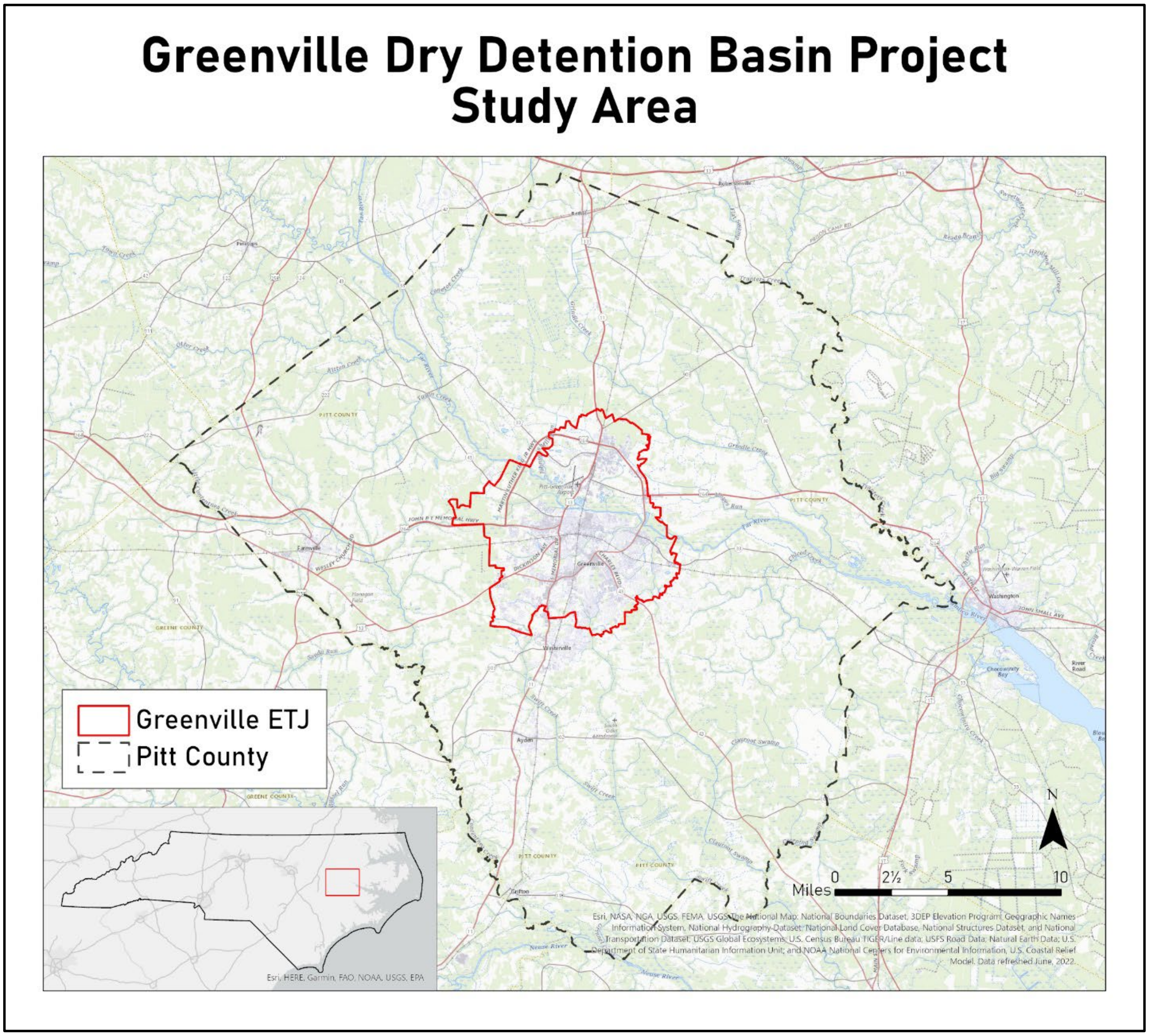

Figure 6 - Map of the Greenville DDB Project study area. The Greenville extra-territorial jurisdiction is shown in red. Map created by the author.

Greenville is the seat of Pitt County, North Carolina, located centrally in the state's Coastal Plain. The city is home to just under 90,000 residents as of 2020 (Census, 2020). Greenville is the home of East Carolina University, a public education institution which draws over 20,000 full-time students to the city (ECU, 2022), many of whom are not counted toward local population but still rely on the infrastructure and services in the area. The City's largest employers are ECU Health services (formerly Vidant) and the University itself. Greenville attracts many workers from nearby communities to the multiple medical, pharmaceutical, scientific, and manufacturing companies in the area. This project is concerned exclusively with the area contained within the Greenville ETJ (**Figure 6**); this specifically excludes the communities of Winterville and Simpson, which border the ETJ on the south and east, respectively. Greenville is bisected by the Tar River, with many of the area's industrial and manufacturing sectors in the north, and the city center to the south (**Figure 7**). The Tar River becomes the Pamlico River after reaching Little Washington (approx. 20 miles to the east), which then becomes an estuary of the Pamlico Sound. The region experiences warm, humid summers with cool winters; from 2017-2022, the average maximum daily high temperature for July was 90.7°, and the average minimum daily temperature for January was 33.1°F (NOAA, 2023a). From 1991-2020, Greenville's wettest months were September, August, and July, with normal monthly precipitation accumulations of 7.3in, 6.01in, and 5.87in, respectively (NOAA, 2023b). Greenville sits at an elevation of 56ft (US Geological Survey, 2000). The Tar River's first flood stage measures 13ft, with a major flood stage at 19ft (National Weather Service, 2023). Greenville's terrain is generally flat, with low swamps and wetlands covering a wide swath parallel to the Tar River (especially on the northern banks). There are multiple natural streams that branch off of the Tar, which divide the City into seven local watersheds (**Figure 8**). Greenville sits within the Tar-Pamlico River Basin, and therefore complies with the water quality practices (including stormwater management) outlined in the Tar-Pamlico Basinwide Water Quality Plan (NCDEQ, n.d.).

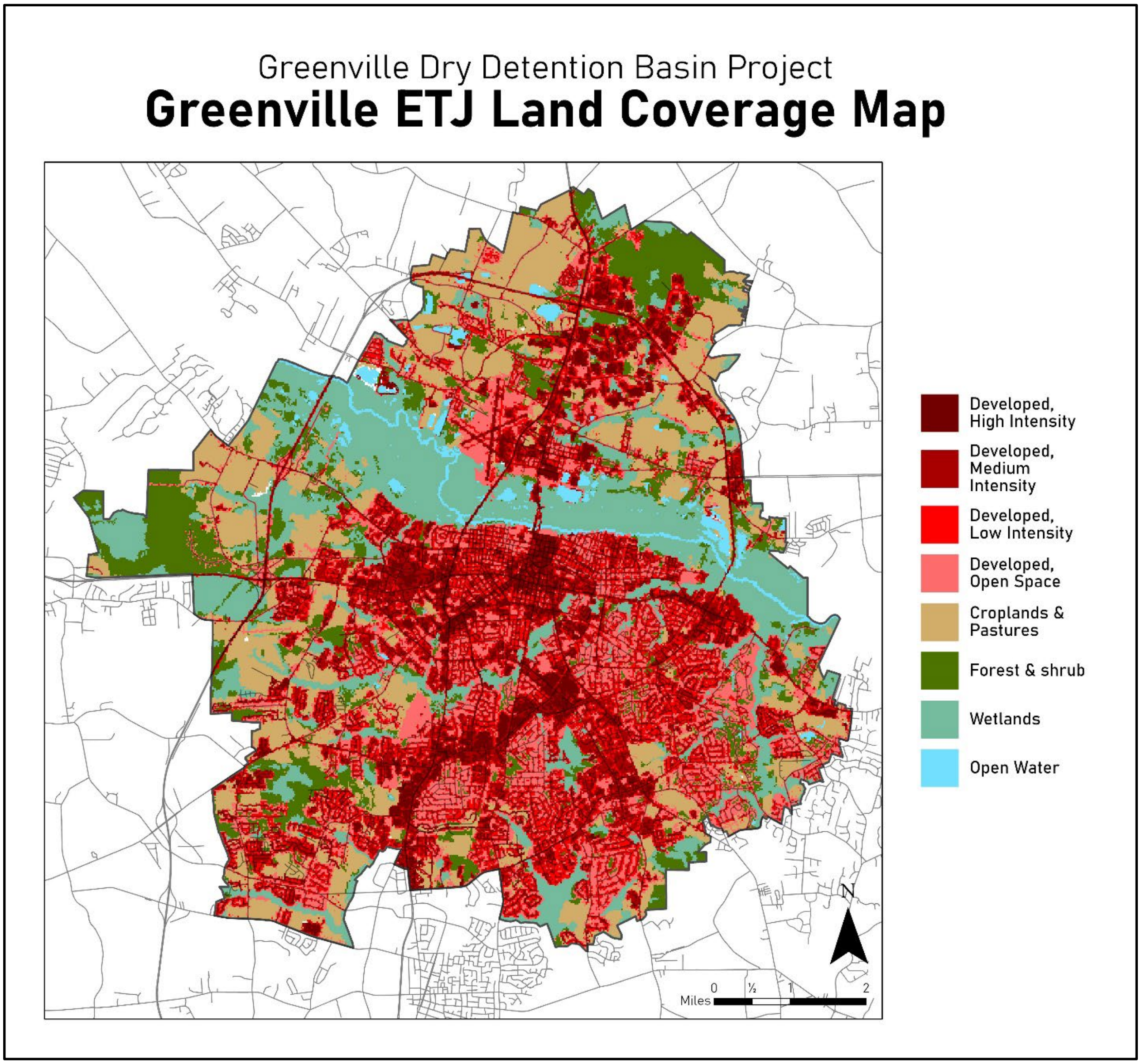

Figure 7 - Greenville ETJ Land Coverage Map. Greenville is a highly developed urban area, divided through the middle by the Tar River. Map created by the author using information from the National Land Cover Dataset.

Generally, Greenville sits on very low land above a shallow water table. The marshes and swamps in the area contain many thousands of naturally formed depressions that will need to be excluded from evaluation. Fortunately, most of these depressions are located either in the natural wetlands that skirt the Tar River, or along the smaller tributaries and streams that flow through the city.

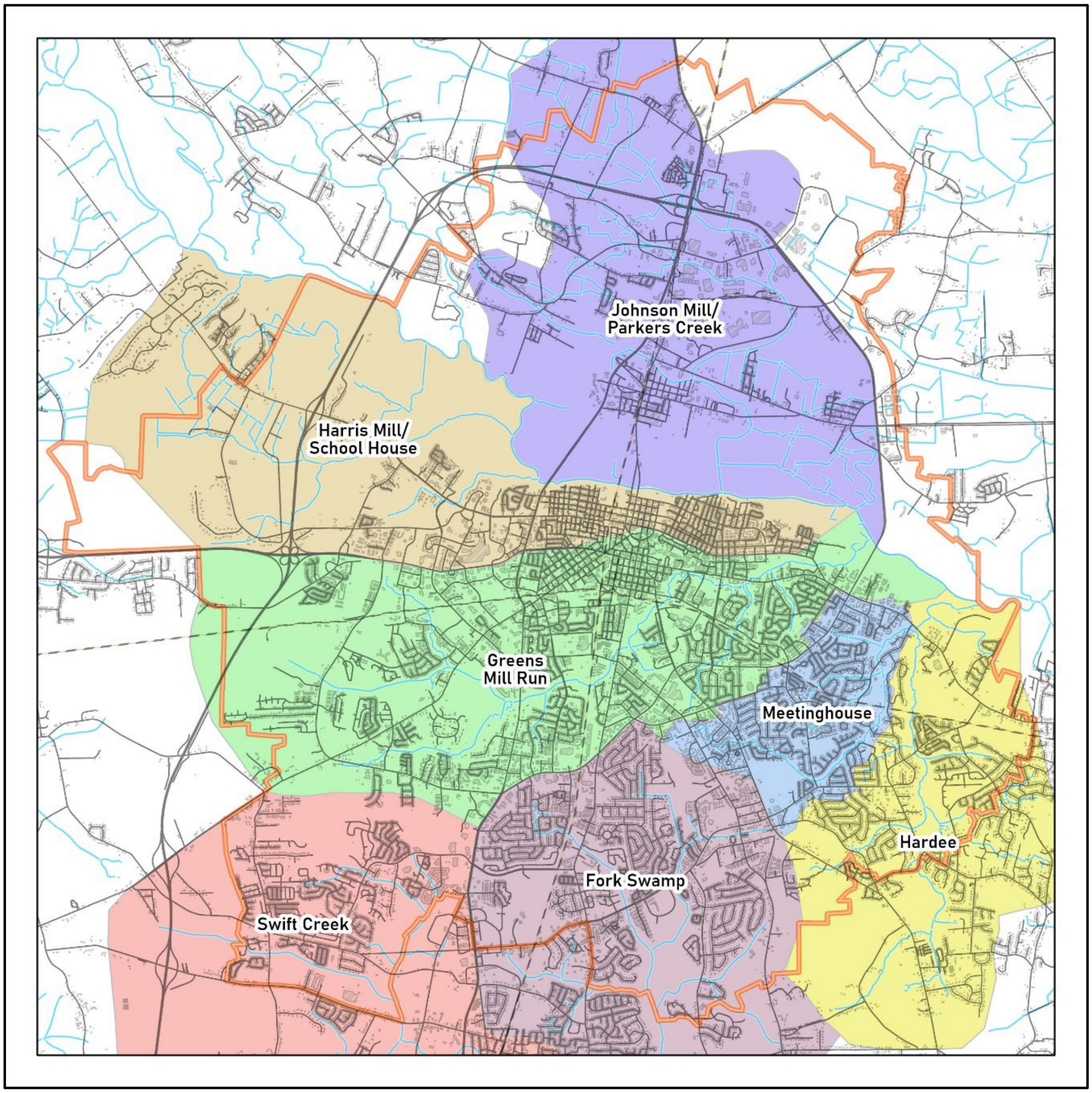

Figure 8 - Greenville ETJ watersheds. Map created by the author. Data provided by Greenville GIS Department.

4.2. Technical Overview

The primary project goal of the GIS team and this GRA position can be summarized in the following statement:

> *Perform feature detection analysis of Greenville's SCMs using LiDAR imagery. The analysis should identify nested surface depressions and provide predictions for dry detention basins. Predictions should be accurate enough to provide a verifiable list of DDBs to be included in future retrofit analysis.*

This research objective is a critical requirement for continuation of the project. The planned execution is known to be a viable approach; other endeavors to map stormwater networks have been executed in similar ways, and similar GIS applications have been implemented before. This chapter discusses the iterative evolution of the approach and the execution of tasks required to ensure the objective is successfully met. A detailed description of the methodology discusses the development of the GIS and the output of the application.

4.2.1. **GIS enables remote analysis.** GIS is the use of computer-based processes to visualize, analyze, and store georeferenced information. Common GIS products include maps, geospatial analysis reports, and geospatial databases. GIS provides the tools for easy exploration, analysis, and visualization of spatial problems, including urban planning issues. It can be used to create detailed maps and 3D models of a community, to track changes over time, to compare data from different locations, and to display planning proposals with a low time-cost. In everyday planning applications (such as would be expected in a municipal GIS department, for example), GIS is used to maintain databases of addresses, utility infrastructure, emergency service coverage, and more. In research applications, GIS is a powerful and flexible framework for performing geospatial analysis. For the Greenville DDB Project, GIS allows the project team to use pre-existing remotely sensed data to detect surface depressions, characterize and separate potential DDB features, map the identified candidates, and map the newly catalogued basins.

The planned approach to address this research objective is shown in **Figure 9**. A LiDAR-derived digital elevation model (DEM) is used as the primary input layer. A contour layer is generated from the DEM; this layer will indicate depressions throughout the study extent, and these contours will be the features for which spatial attributes are calculated. A relational database engine is used to remotely store and access the data being analyzed in this scenario. It should be noted that a relational database is not explicitly required for this analysis, but this approach facilitates easier sharing and processing of data. After DEM contouring is completed, a data table is initialized and spatial attributes are calculated for each closed contour, including the grouping of nested contours into stacks. The attributes for each stack become classification nodes in a random forest (machine learning) modelling algorithm. The algorithm determines stack classifications by comparing attributes against a sample of known DDBs (a “training” set) and generating a binary prediction.

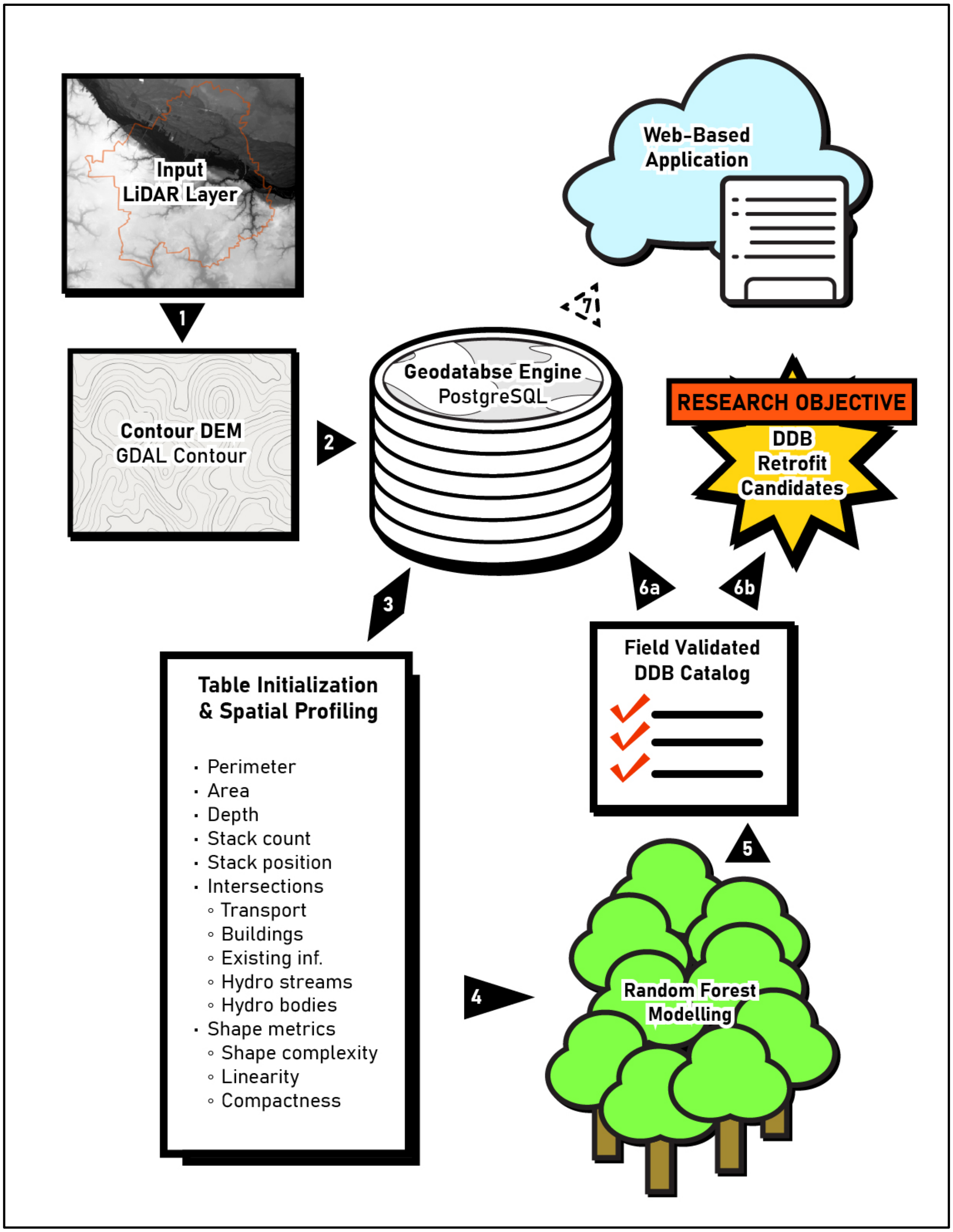

Figure 9 - Conceptual workflow of GIS development. 1) An input LiDAR DEM forms the basis for a 2) contour analysis which is held in the geodatabase. 3) Spatail profiling is performed on the contour layer, and output is stored in an initialized data table. 4) The contours are subjected to a random forest algorithm, which classifies candidate features by comparing against a training dataset. 5) Candidate features predicted as DDBs by the RF algorithm are compared against orthoimagery and a field validation is performed. 6a) The model results are stored as a view in the geodatabase, and 6b) the field validated DDBs are entered into a retrofit-candidate list. Steps 3-6 are repeated as necessary. 7) In the future, it may be possible to provide this service as a web application for other municipalities with similar needs. Figure created by the author.

Because the calculated spatial attributes for each stack form the basis of the machine learning approach, selection of appropriate spatial characteristics is of maximum importance. Greenville's DDBs are not uniform in layout, construction, age, capacity, or placement relative to their respective catchment area. An exploration of expected spatial characteristics forms the initial approach to detecting these features, but field verification is necessary to update and expand classification characteristics. Iteration is fundamental to maximizing the prediction accuracy of the model. This approach is based on a circular feedback loop of characterization, prediction, and validation.

4.3. GIS Application Development

This section discusses the development of the DDB identification application and is presented in two parts: the evolution of the GIS programming, and the iterative improvement of the model output. Because the successful development of the GIS was a crucial milestone for the rest of the project, the entirety of the GIS programming for the application was performed by Mr. Howard. Technical considerations and feedback were provided by the author, but Mr. Howard’s extensive expertise in the field of GIS programming was required to ensure that the product was delivered in an acceptable condition and timeframe. The conceptual execution of the GIS programming is presented herein; for a sample of the GIS script, see **Appendix 4**.

4.3.1. **GIS development environment.** While desktop suites like ArcGIS and QGIS provide excellent environments for visualizing data and performing geospatial analysis, GIS programming enables a developer to perform complex computations of large datasets with more flexibility and ease, and in shorter timeframes. A geospatial database was established as a repository for the data to be processed and the resultant output of the GIS approach. Because the geodatabase is intended to be shared with the City of Greenville, and because the analysis relies on input LiDAR data from other state agencies, PostgreSQL was chosen as the relational database engine for this application. Relational database engines are systems that provide the ability to store, manage, and query large databases, and are intended to be a complete solution for managing data. PostgreSQL is an open-source object-relational database management system that has been used for data warehousing, web development, and business analytics (PostgreSQL, 2023). PostGIS is a spatial database extender that allows PostgreSQL to interact with geospatial objects, and is a necessary part of this analysis. PostgreSQL relies on the SQL programming language to perform data management and analysis. JetBrains DataGrip and DataSpell were the integrated development environments used to generate the programming code. A Python notebook was used to store and access the random forest machine learning tools used to classify the depression stacks.

4.3.2. **Predicting DDBs with LiDAR imagery.** The North Carolina QL2 LiDAR DEM forms the basis of this analysis. This DEM was generated on behalf of the North Carolina Department of Emergency Management in 2014 and provides a spatial resolution of approximately 3 feet in unvegetated terrain (NCDEM, 2014). After selecting the appropriate quality DEM, a contour analysis was performed. GDAL is an open-source library for raster and vector analysis tools. The *gdal_contour* tool (GDAL/OGR Contributors, 2022) was referenced from this library and used to generate vector contours for the input DEM. Contours were measured at elevation intervals of ½ foot, which generated more than 20 million features. This interval was chosen in order to effectively capture potential depressions in enough layers. Though the SDM doesn't describe a minimum depth of the temporary pool, it can be no more than ten feet deep. One-half foot was used selected as an appropriate interval, though shallower DDBs may be better captured by a smaller interval. Contour rings that do not close within the extent of the analysis area and closed rings of negligible size ("specks") were removed from the dataset and the remaining features were stored in the geodatabase. Other necessary data layers are stored in and referenced from the geodatabase as well, such as hydrography, transportation, building footprints, and soils.

Using SQL, a pre-modelling script was developed that initializes/updates the data table used for attribute collection, and performs spatial characterization for each contour. Spatial characteristics are largely broken into three categories: basic attributes, intersections, and shape metrics. Basic attributes include common spatial characteristics like perimeter, area, depth, elevation, and volume. Crucially, this cluster of geospatial analysis includes grouping contours into stacks and assigning parent/child relationship attributes. This allows the GIS team to evaluate entire depressions, not just elevation rings. Intersection attributes are calculated for the contour stacks; these calculations indicate which feature stacks intersect with certain other features like roads, streams, or building footprints. These previous examples eliminate candidate stacks from classification, though not all intersections will do so—DDBs that have been properly implemented will have two inlet/outlet features, for which the SQL script accounts. After accounting for general physical characteristics and intersections, the script performs shape profile calculations on the contour stacks. Shape profile metrics include complex attributes such as perimeter-to-area ratio, volume-to-area ratio, and fractal dimension.

4.3.3. **Random forest modelling.** After performing spatial characterization of the contour stacks, the data are entered into a random forest machine learning algorithm. A random forest algorithm works similarly to a decision tree by making classification predictions based on sequential decision nodes. However, a random forest randomizes and repeats the tree several times, leveraging the law of large numbers to create a more reliable prediction; specifically, it reduces overfitting and variation in the predictions, which are common problems for decision tree models. The random forest model relies on a training dataset to measure the characteristics of already-confirmed features, then makes classification predictions based on a sequence of decision nodes (this is a single decision tree). The known features are randomly divided in half—one half becomes the training dataset; the other half is designated as the validation set. Features in the validation set are incorporated into a sample of features from the dataset to be classified (the contour stacks), and all features are given a binary classification (DDB or non-DDB). The division between the training dataset and the validation dataset is randomized each time ("random"), and the prediction is made many times over (a "forest" of decision trees).

The spatial attributes used to characterize the contour stacks within the model are of key importance. As the model makes predictions, the order in which attribute fields are used for decision nodes is determined by entropy; the decision nodes that generate the greatest difference in classification determination have the highest entropy, and are used earliest in the decision tree. Entropy is calculated during evaluation of the decision nodes and is affected by the average characteristics of the training dataset. By randomly selecting the training dataset during initialization of each decision tree (a process referred to as bootstrap aggregation, or "bagging"), the order of entropy is slightly shifted each time. Essentially, each decision tree in the random forest model will evaluate the spatial characteristics of the training dataset slightly differently, and thus will predict the classification of each unknown feature with slightly different confidence. After running the appropriate number of simulations (usually in the thousands or more), the predictions for each contour stack are tallied in a simple majority vote. The predictions for the validation dataset hidden in the unknown features are compared to their real-life classification, and an accuracy rating is generated for the model run. As long as the model results in an acceptable overall rating, the contour stacks predicted as DDBs by the random forest model are sorted into a new table of selected candidate features.

4.3.4. **Field validation.** Performing field validations is vital to the success of the GIS application. Even with a very high level of reported accuracy, the model can make false-positive predictions. A physical check of the predicted DDBs is necessary to eliminate false-positives and to expand the known DDB list—which therefore expands the training and validation datasets. Additionally, field validation provides the opportunity to observe trends across the predictions and collect preliminary on-site data for retrofit prioritization.

For the purpose of refining the GIS application, field validations need only consist of a simple visual inspection of the predicted feature in-situ. After the first round of predictions made by the RF model, I personally performed field validations on a sample of predicted features (see §5.1.2 for further details). This process can easily be accomplished by an individual, as a simple visual examination of the depression stack for functionality as a DDB is enough to validate the model's predictions. Positively identified DDBs are classified within the main contour layer as known-DDBs, and false-positives are classified as known non-DDBs.

It should be noted that field validation is a discrete process from field surveying. The former are simple visual checks to ensure the accuracy of the RF model's predictions, while the latter are in-depth inspections of verified DDBs. Validation can be performed for a large selection of DDB predictions by a single individual within a matter of hours. The full field survey process involves the recording of specific DDB conditions, the capture of geospatial data regarding inlets and outlets, and the evaluation of the practical catchment area of a given DDB. Field surveys are best performed by a small team in order to generate a consensus on the best potential retrofit for each DDB. Field survey procedures were developed by members of the Center for Watershed Protection, who will train ECU team members on how to properly execute survey procedures for additional DDBs identified in the future (see §5.3.2).

5. Results & Discussion

5.1. Technical Output

Though the concepts of this application are rather straightforward, the programming script has been fine-tuned as it has undergone development. The development process itself is exploratory in nature, as the model requires incorporation of additional shape metrics in order to gain greater prediction accuracy. It is not enough to settle on a single prediction output. The process is iterative, and each output must be considered carefully and used to refine the model. As such, the iteration itself is part of the result of this approach. The application is effective at identifying engineered depressions throughout the jurisdiction, but effective differentiation between SCM types is still being developed.

5.1.1. **Narrowing the selection.** After the initial ½-foot contouring of the LiDAR DEM, slightly over 22 million contour rings were captured. After eliminating unclosed features and contours with a total perimeter length of less than 100 feet (these features are considered noise by the GIS developers), 1.2 million contours remained. After constraining the data to the extent of the Greenville ETJ and accounting for invalid feature intersections, the dataset was reduced to approximately 115,000 total contour rings. By the middle of October, the model had reduced the predicted DDB count to 22,000 features. This was early in development, and thus far the specific attributes used to train the model were as follows:

- *stack_position:* a measure of where a contour lies in the stack order
- *stack_depth:* a measure of the depth of a contour within the stack (not elevation)

- *ix_drop_inlet* and *ix_yard_inlet:* which shows intersections with inlet/outlet features
- *ix_parcels:* a measure of the number of parcels a contour intersects
- *sm_par:* the perimeter-to-area ratio of a contour
- *sm_sci:* the shape complexity index of a contour
- *sm_fractal:* the fractal dimension of a contour
- *sm_linearity:* a measure of a contour's ratio of length to width

These shape characteristics were helpful in reducing the overall number of candidates, but it wasn't enough to allow the process to move on to field validation. At this time, contours were being

Figure 9 - Example: early prediction results. Predicted DDB contours are shown in green, with all contours in white. As seen here, early model runs evaluated individual contours instead of stacks, which resulted in multiple predicted DDBs in the same depression.

evaluated on an individual basis, without accounting for any relationships between contours from the same stack. This proved to be problematic, as each contour within a given stack would be evaluated by the model and predicted as a DDB (**Figure 10**). By training on individual contour rings instead of entire stacks, the model was making direct comparisons between the single polygon features that were manually digitized (the known DDBs) and the millions of natural contour features throughout the area. Additionally, at this point the validation set consisted of an equal number of known DDBs and selected non-DDB contours, which gave the model relatively few examples of what a DDB does *not* look like.

Reflecting on these limitations allowed the GIS team to make further adjustments to the process. With millions of naturally formed contours in the DEM, the team realized that a random selection of unidentified contours would have an incredibly low likelihood of selecting any actual DDBs, so the validation dataset was expanded with a random selection of 500 contours. In order to avoid predicting multiple DDBs within the same depression, all contours that were completely contained within a parent contour were dissolved, meaning the model would only make predictions on the uppermost ring of a stack. The contour stacks had also been reduced enough in number to perform volume calculations for the entire stack, which significantly helped in characterizing DDB features, like slope angle. Two new shape metrics were calculated in relation to the volume metrics:

- *rm_fcar:* the percent change in area between a contour and its first child
- *rm_acar:* the average percent change in area between a contour and its children

These metrics provide insight to the shape relationships between the uppermost contour of a stack and the contours below it. In engineered DDBs, the side slopes are meant to be uniformly graded; a depression with steady side slopes should show very similar measures between these two metrics. Most importantly, while shape profile calculations were still performed on all contours, the model would now only make predictions based on the uppermost “parent” contour of a particular stack. This provided a much better basis for the model to evaluate the range of possible shape profiles within the dataset. After these changes, the random forest model was able to generate a DDB prediction list of 518 stacks with an accuracy rating of 96% when compared against the training dataset.

5.1.2. **Field validation.** The original estimate of SCMs throughout the city was given to be somewhere between 300-400. With a prediction count of 518 depression stacks, it was determined that the GIS had progressed enough to begin performing field validations. The random forest model isn’t limited to a certain number of contour stacks that it can predict as DDBs, and with 518 predicted DDBs in this case, performing field validations on every candidate feature was not an option. In order to meet the objective of providing an actionable list of retrofit candidates by the beginning of 2023, it was decided to sample roughly 10% of the predicted DDBs.

The output list of model-predicted DDBs was compared against recent aerial imagery of the area, and contour stacks that overlayed visual indicators of real-world DDBs were added to a “hand-picked” list of verification sites. Priority was given to the candidate features determined most likely to be true DDBs in order to expand the training dataset. As seen in **Figure 11**, some of the predicted features could be excluded simply for their shape alone. Some candidates exhibit the kind of perimeters that indicate natural formations, which DDBs are not. The size of certain features also seems to indicate non-DDB features which may have similar spatial profiles but are otherwise too large. For example, irrigation ponds are shaped very much like large DDBs, but do not serve the same purpose. Still other candidates showed very long and narrow profiles, which strongly indicate roadside ditches. Again, these can have very similar spatial attributes as DDBs, but serve a different purpose. After considering the overt shape indicators of the predicted DDBs, the team chose to perform field validations for features that were relatively small, smooth-sided, and located near the kinds of development where DDBs would be expected to have been built.

A sample of 56 DDBs was compiled into a picklist, and during late December and early January the author performed field validations for all selected sites. Of the 56 predicted DDBs, 39 were true DDBs, 12 were false-positives, and the remaining 5 were neither able to be confirmed nor denied. The model provided an accuracy rating of 96% compared to the training data, but ground-truthing of the sample picklist had resulted in a real accuracy rating of 69%. Despite this difference, the GIS application had met the basic requirements of the overall research objective by successfully predicting DDBs from remote sensing data. The 39 positively identified, field validated DDBs were then reduced once again to a short-list of 25 features and presented to the project team in January for further retrofit appraisal (**Figure 12**).

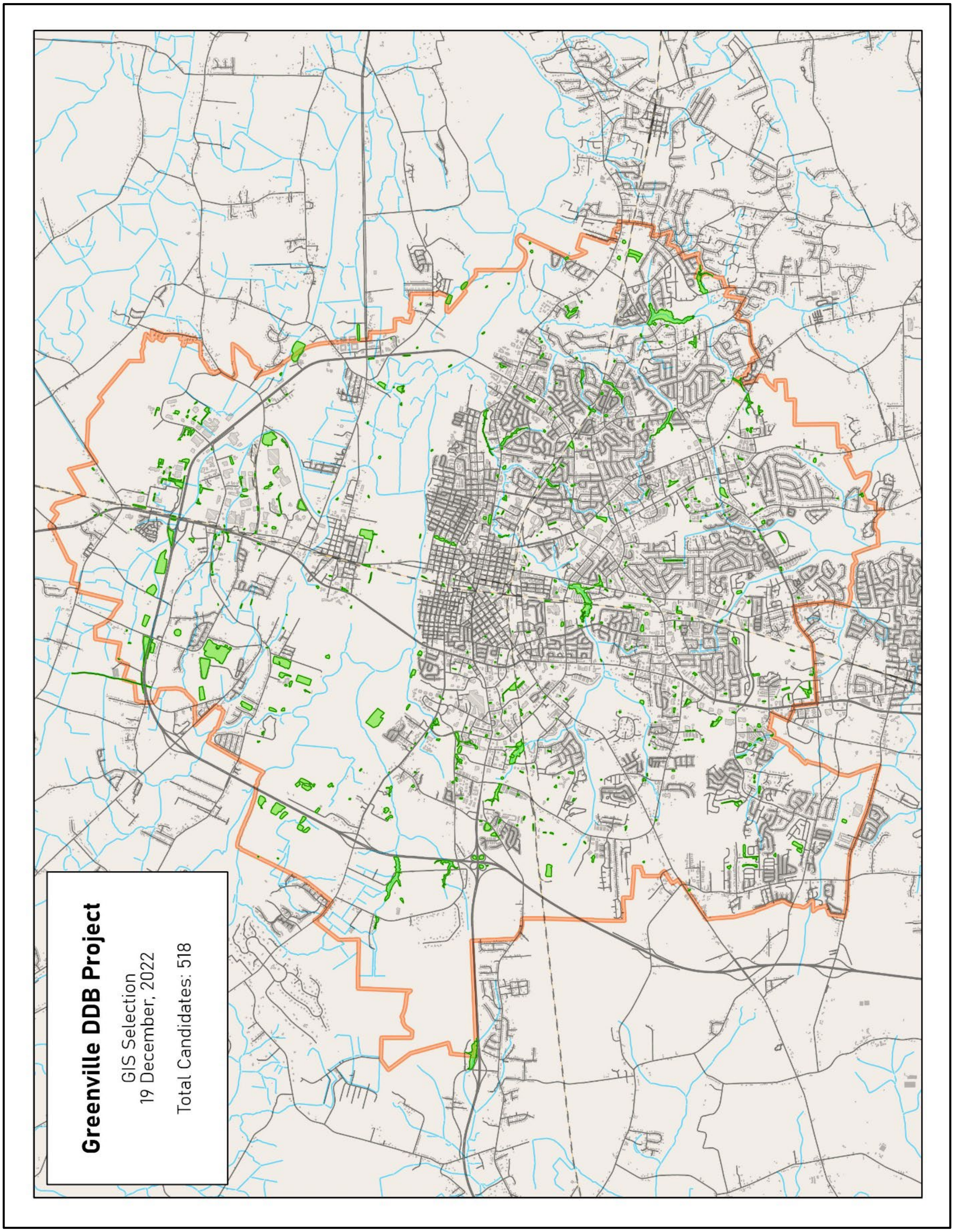

Figure 10 - Random forest DDB predictions, December 2022. The 518 nested depressions predicted as DDBs by the random forest model are shown in green. Map created by the author.

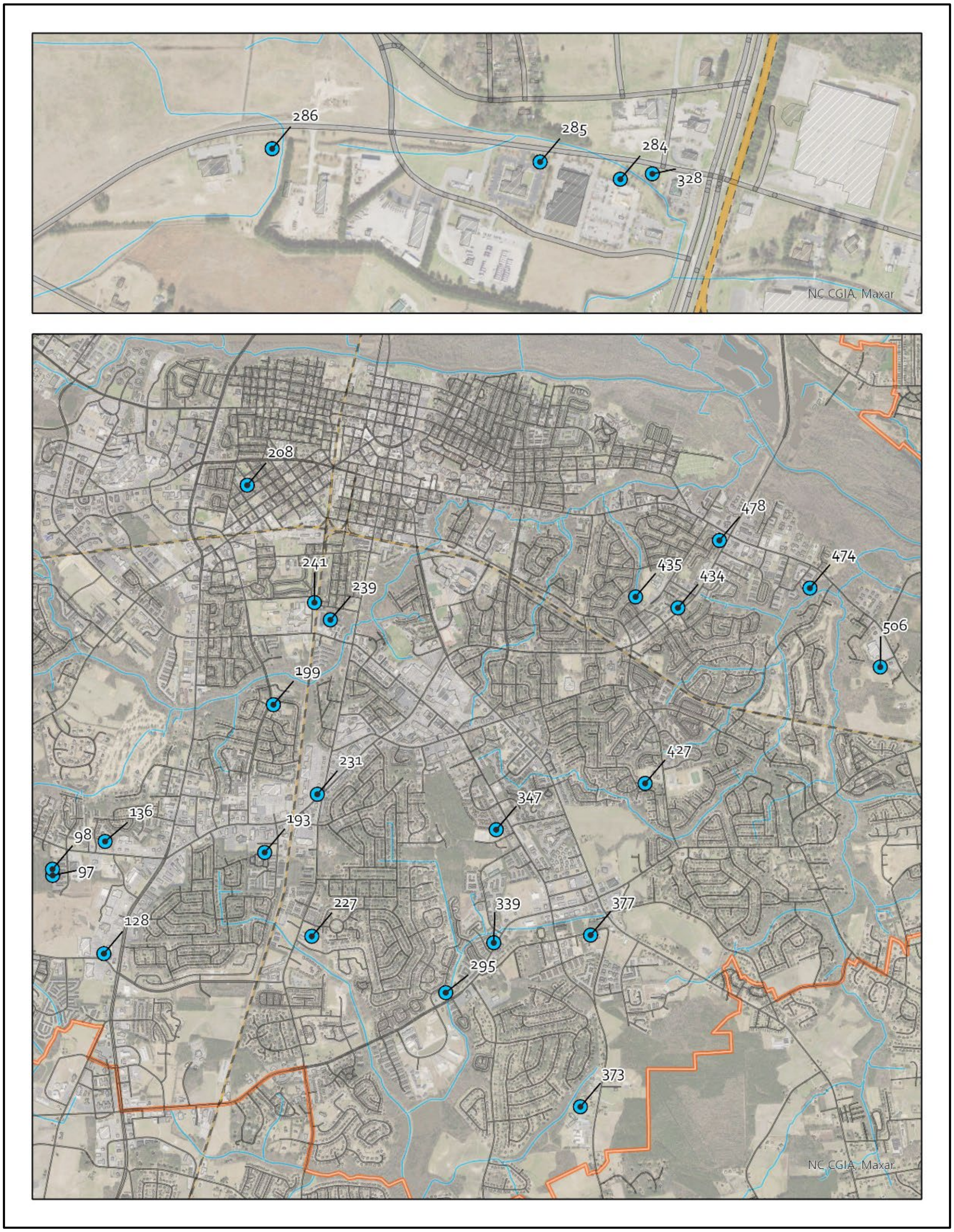

Figure 14 - The final selection of field-validated DDBs. DDB features are identified by the ID number assigned to the uppermost contour of the stack. The upper frame shows a small selection from the northern side of Greenville, while the lower frame shows the selected majority in the city proper.

5.2. Continuing Development

Considering the limitations listed previously, the GIS team finds it worthwhile to continue development of the GIS application. The following subsections discuss further ways the process can be improved.

5.2.1. **Identifying DDB retrofit candidates.** The 39 confirmed DDBs were winnowed to a prioritized list of 25 DDB retrofit candidates that was presented to the project team in January. These candidates will be surveyed by team members from ECU and the CWP in early May 2023, during which they will undergo close inspection for suitability for retrofit. However, these 25 DDBs represent only a small fraction of the total expected number of DDBs throughout the Greenville ETJ, and do not necessarily represent the most viable retrofit candidates in the area. As discussed throughout this report, the Greenville DDB Project is intended to establish a process for identifying, cataloguing, and evaluating DDBs in order to provide support for future retrofit proposals. It is not within the scope of the project to make a direct selection of DDBs to be retrofit, nor even to make the actual retrofit proposals. It will be left to Greenville's Stormwater Management Department to decide what retrofit projects to invest in, if any. It will be in the City's best interest to conduct a thorough evaluation of the majority of its SCMs in order to determine which are most fit for future development. To that end, the GIS team is interested in the continued development of the application.

In accordance with the primary objectives of the project at-large, the GIS has resulted in a process capable of assessing nested depressions throughout the Greenville ETJ and providing a high-confidence prediction of which features are expected to be engineered DDBs. Because DDBs generally make for the best retrofit candidates when compared to other classes of SCMs, the GIS has been trained to observe and make predictions based on spatial attributes that are associated most closely with DDBs. The GIS compartment believes that it will be worthwhile to shift the GIS analysis from a binary yes/no prediction of DDB presence to a methodology that predicts a range of SCM classification types. This will be of great use in cataloguing all of Greenville's SCMs and will likely improve the accuracy of DDB predictions in particular.

When determining which characteristics to include in the random forest modelling, the shape metrics that resulted in the most significant prediction impact are compactness, stack depth, linearity, and volume. The training dataset against which the prediction candidates are measured consists almost entirely of known DDBs, not other types of SCMs. Essentially, the GIS is trained to look for depressions of fairly rectangular shape, with smoothly contoured side slopes and two inlet/outlet structures. This is the result of several modelling runs where each new pass added at least one more metric that focused on typical DDB profiles. However, during early field verifications it was realized that the GIS was quite adept at predicting most of the engineered depressions in the area, including roadside ditches and wet ponds. After all, these features are nearly identical to DDBs from a superficial level; they all have smooth side slopes with multiple inlet/outlet features and high compactness ratios. Eliminating ditches from the modelling predictions was a matter of including linearity as a factor, as the bounding box for these ditches tends to be very long and narrow compared to a DDB. The GIS team finds it reasonable to believe that additional shape metrics could be included that relate to typical profiles of other SCMs throughout the area, and providing a training dataset with a reasonable sample of know non-DDB SCMs could result in a more diverse prediction scheme that may be capable of identifying ditches, ponds, and swales. A major caveat to this, however, is that Greenville has proportionally far fewer of these other SCM classes—perhaps not even enough for an acceptable training dataset.

5.2.2. **Additional input data.** Not all SCMs can be easily characterized by their shape, either. Wet ponds, for example, are structurally identical to DDBs with the exception of their being filled year-round. The LiDAR DEM that was used for the DDB detection method relies on bare-earth topography to detect depressions, but it does not account for depressions which may be vegetated or filled on a regular basis. There were a few wet ponds that were regularly and falsely identified as DDBs during the development process because they were empty or low during the collection of the LiDAR data. Having some way of evaluating the change in surface pooling after a major storm event could form the basis for a comparative analysis that could in-turn be factored into a SCM-type classification model. Synthetic aperture radar (SAR) is a method of collecting remote sensing data even during times of inclement weather—a capability that LiDAR lacks. SAR has potential value to this GIS as a way of providing surface data during and immediately after a storm event when SCMs condition is most critical. With SAR data, it is feasible that the model could be trained to look for depressions that fill from empty after collecting surface runoff and compare those against depressions that increase in water level but do not drain.

Additionally, some of the DDBs that were predicted by the GIS were indeed DDBs at one point, but have slowly developed into ad-hoc wetlands over the decade since the LiDAR was flown. Stormwater wetlands are SCMs that have specific vegetation that aids in filtering pollutants out of stormwater runoff, so it is important to understand what vegetation has grown in naturally and what additional species may be introduced to improve filtration efficiency. It is not beyond the realm of possibility that some old DDBs may have entirely changed shape since their implementation and become completely overgrown. Near-infrared (NIR) imagery has been used extensively to evaluate vegetation cover, and the inclusion of a NIR layer could facilitate a vegetation-based comparative analysis approach.

Perhaps most obviously, a newer input DEM would likely provide a much better basis for prediction. The LiDAR DEM provided by the NC Department of Emergency Management is very nearly 10 years old at the time of writing. Many areas in Greenville have changed radically since 2014. For example, the GIS model predicted a large DDB just south of the ECU coliseum, but the area has been entirely paved over and the depression no longer exists. The US Geological Survey is currently performing aerial LiDAR survey flights, with new DEMs expected to become available sometime in 2024.

5.2.3. **Potential web application.** Many other communities throughout eastern North Carolina (and other coastal regions of the US) could benefit from an SCM identification tool. It is possible that a web-accessible application based on this methodology could allow other agencies to conduct analysis for their own respective jurisdictions. In a hypothetical scenario, a user could provide their own input contour dataset (or perhaps even their own DEM) which would be run through the random forest model, resulting in a high-accuracy SCM prediction output. This could allow other communities to perform an evaluative inventory of their own stormwater network, and begin to consider retrofit possibilities if needed.

5.2.4. **Further applications of the GIS.** During early discussions concerning the available stormwater infrastructure data from the City, it was noted that often times large impermeable surfaces can be used to detain stormwater. For example, large parking lots in areas like shopping malls can be implemented with an intentional slope towards a central inlet, and the entire lot will serve as a wide, shallow detention basin during times of heavy precipitation. These parking lot basins serve as DDBs, but their spatial attributes make them radically different than engineered standalone DDBs. Because of these spatial differences—in addition to the impracticality of retrofitting an actively-used parking lot—parking lot basins were not incorporated into the shape characterization algorithm, and the GIS team did not expect to be able to map them. However, during the development of the GIS, the team realized that they had inadvertently found a methodology for identifying the central drainage points for these kinds of parking lot basins, and therefore had discovered an effective method for predicting them.

Figure 13 displays a map of parking lot basins in one of Greenville's commercial districts. These nested contour rings—highlighted in red—were identified by the random forest model as DDB features. Though these are not the kinds of SCMs the project is looking to evaluate, their identification has proven useful anyways. The blue triangles in the image reflect the lowest elevation point within the contour stack. These points do not explicitly identify drain inlets, but the GIS team finds it probable that they correlate closely with actual inlet placements. As a byproduct of the DDB search application, the GIS team has very likely mapped a significant number of parking lot DDBs. With enough time, this process could also be refined to provide a more complete inventory of parking lots basins.

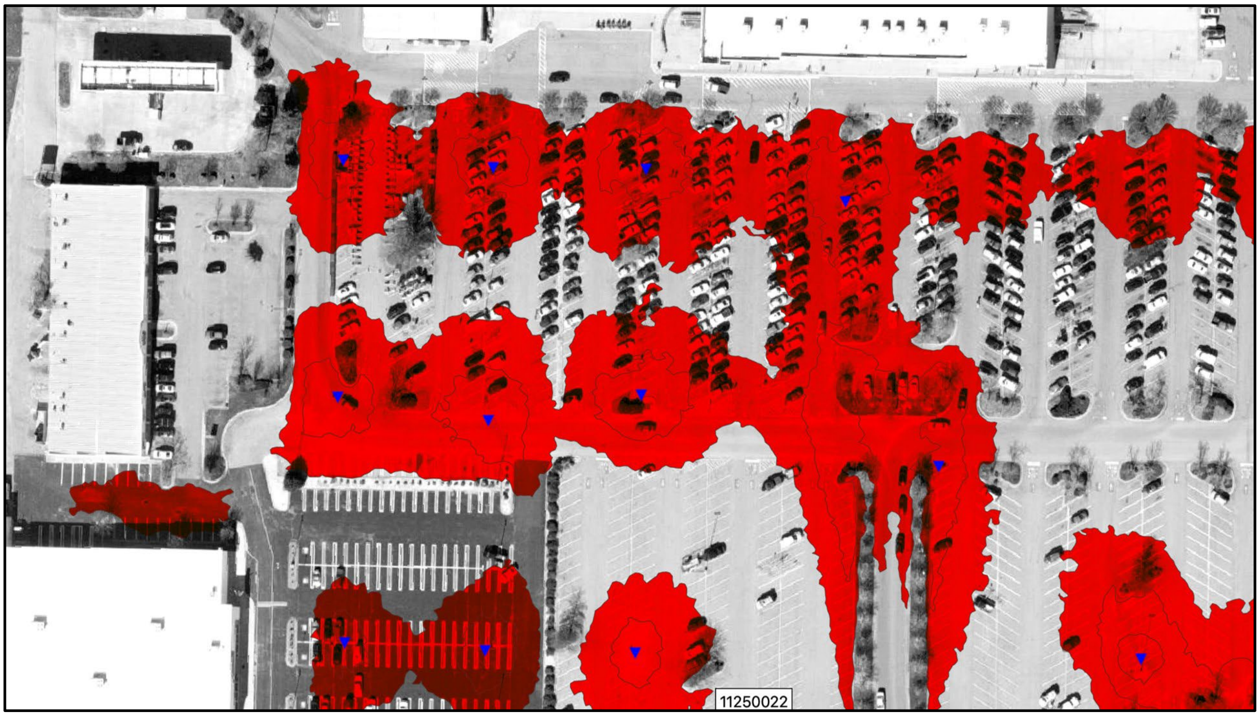

Figure 18 - Parking lot basin drain predictions. This image shows depression stacks in red, with the lowest elevation in the bottommost stack visualized with a blue point marker. It is suspected that these markers likely correspond to drain inlets. Image produced by Rob Howard.

5.3. The Future of the Greenville DDB Project

5.3.1. **Retrofit prioritization.** At the time of writing, the project team is actively developing a prioritization matrix for the DDBs. A prioritization matrix will allow decision-makers to evaluate each DDB according to a weighted array of retrofit criteria. For example, because the City receives NEPA credits for improvements to the overall filtration capacity of the stormwater network, the Stormwater Management Department may choose to prioritize filtration improvement over capacity improvement or retrofit cost. There are many factors that need to be considered when making proposals for improvement projects like SCM retrofitting, so the prioritization matrix needs to capture as many of these factors as possible.

The GIS process has already captured many physical attributes that will be useful for retrofit prioritization. Overall size (perimeter, area, volume) is important to consider, as larger basins make for greater filtration capacity and easier retrofit implementation. Physical placement will also need to be considered; a DDB on municipal property will be easier to access than one on private property. Aside from physical characteristics of the DDBs themselves, however, there are other external characteristics of the potential candidates that need to be accounted for.

Some of Greenville's underserved communities are located within the city's floodplain; improving individual SCM efficiency should improve the localized effectiveness of the stormwater network, and may help reduce future flood risk for these communities. While the GIS development team has been identifying potential DDB candidates, Dr. Iverson has been engaged in a socioeconomic analysis of Greenville's neighborhoods so as to get an understanding of which DDBs may be able to reduce flood risk in these areas. As a reminder, the EEG Program favors projects that create improvements in underserved and at-risk communities, and Greenville's history flooding has typically been most concentrated around the communities nearest to and north of the Tar River. The prioritization matrix will include an evaluation of the relationship between DDB candidates and the relative flood risk of their surrounding neighborhoods.

When DDBs are transformed into Primary SCMs, the capacity for filtration improvement is greatly enhanced when the selected DDB exists in soils with good drainage capacity. Improving DDBs that are located over well-drained soils will have a greater return-on-investment upon being converted into primary SCMs. Dr. Iverson has been conducting a soil analysis of the areas surrounding the candidate DDBs, which will allow the priority matrix to account for this factor. Total catchment area is also being evaluated, as this will affect both filtration capacity and potential flood risk reduction.

5.3.2. **Field surveys.** The CWP team will be coming to Greenville to conduct in-depth evaluations of the proposed candidate DDB sites in early May. These professionals have extensive personal experience with evaluating retrofit potential of SCMs, and will be key in understanding the practical engineering aspects of prioritizing the selection. Over the previous few months, the CWP team has been developing a field survey protocol for evaluating SCM type, inlet/outlet condition, erosion, basin layout, berm structure, and practical constraints. Members from the CWP and ECU will visit all DDB candidate sites and establish a baseline approach for surveying. After the CWP team returns to their home office, the remaining ECU team members will be able to continue surveying additional candidate sites as needed. In the future, additional surveys may be needed for DDBs that have been approved for further analysis. These efforts could possibly involve GPS-RTK, LiDAR, or UAS surveys.

5.3.3. **Future student involvement.** The EEG provides funds for student research positions on the project throughout its duration, but whether additional students will be hired in the future is uncertain at the time. Aside from the author, the project hires one other student researcher who works alongside Dr. Iverson doing socioeconomic analysis. With the critical GIS components completed, it may not be necessary for Mr. Howard to employ a research assistant for the remainder of the project. However, as discussed in earlier sections, the GIS could still benefit from further refinement of the GIS application, more candidate DDBs will need to be identified, and community outreach will need to be performed. The Greenville DDB Project provides an excellent environment for students to gain practical experience in GIS development, stormwater management planning, and civil engineering. In fact, engineering opportunities may prove to be an appropriate attractor for future research assistants, as further prioritization will need to include considerations for the particular retrofit design of a DDB candidate.

5.4. Lessons Learned

Developing a GIS application for the identification of Greenville's DDBs has been both more and less successful than originally anticipated. The relative quickness in which the random forest model could predict SCMs was rather surprising, but the accuracy with which it could predict DDBs specifically was less than we'd hoped for. Previous efforts to identify surface depressions have been successful, but those attempts were usually limited to plucking particular kinds of depressions out from an area where they were expected to be found. The GIS compartment's effort on the project has been to not only identify particular depressions in an area where they could be located almost anywhere, but also to differentiate between different similarly shaped depressions with nearly identical attributes. The GIS team believes that the model is likely as efficient as it can be without incorporating additional layers that will provide data that can't be gleaned from a DEM. The most pertinent consideration that has been observed on the ground is the difference between vegetation density and variety. These differences will be incorporated into the remote analysis in the future.

The importance of subject research cannot be understated, either. The team began their analysis with a good idea of what an SCM would look like in general, but selectively predicting DDBs out of all engineered features has been a matter of understanding the specific differences not in shape, but in composition. The difference between a DDB and a bioretention cell is a matter of inlets, underdrains, and soil compositions; all these things can be detected remotely, but only once they've been identified as differentiating factors. This has been the primary impact of the author's role—to provide the background research needed to inform the proper selection of secondary (non-physical) attributes in the model.

5.5. Limits of the Application

The methodological approach detailed in this report is based on previous successes of remote mapping, but it is a purpose-built application and has its limitations. As stated previously, the particular shape of a single DDB will be inherently different from others, so it is highly unlikely that this approach will be able to identify every single DDB within the study area. The model is adept at picking SCMs out of a series of nested depressions, but there is considerable room for improvement in regard to SCM classification identification. The quality of the output candidates is also dependent on the input data layer. While the resolution of the input DEM is high enough to accurately predict depressions of an appropriate size, it was published nearly ten years ago; having newer or additional input layers of remote sensing data would likely help prediction accuracy. One of the optional objectives of the project is to make this methodology usable by other jurisdictions with similar needs. It may be difficult for a user to fine-tune this kind of GIS programming script to their own study area, especially if they aren't well-versed in the requisite programming languages.

5.6. Conclusion

5.6.1. **What are the best practices for identifying dry detention basins using remote sensing and machine learning?** Throughout the development of this approach, the GIS team has found that the established methodologies for delineating SCMs in an urban area using LiDAR imagery is a valid and worthwhile procedure. Aerial LiDAR imagery is readily available for public use, and there exist a plethora of tools for characterizing depressions in a DEM. This approach discussed herein relies on SQL and Python scripting, but software applications like ArcGIS and QGIS have tools that can accomplish the task as well. Early methods for delineating surface depressions—such as the method outlined in Wang & Liu (2006)—relied on decision tree classifiers to identify specific types of depressions, and the random forest modelling approach detailed in this report is the procedural evolution of that application. By conducting multitudinous executions of predictive classifications, a random forest model can generate a high level of prediction accuracy without incurring over-fitness to the training data. Additionally, as more depressions are positively identified and incorporated into a training dataset, the random forest model should see an increase in prediction accuracy. Much in the same way each of the previous application of GIS-based surface depression mapping discussed in §2.4 has followed a general flow of remote sensing followed by unique characterization of depression features, the development of the GIS application described in this report has required specific tailoring of the GIS programming in order to properly calculate and incorporate the unique spatial characteristics of the different types of SCMs seen throughout the area. Specific research objectives tend to require unique considerations for the specific spatial attributes of the research subject, and this report confirms the value of the flexibility and customization afforded by object-based programming languages.

5.6.2. **How can dry detention basins be differentiated from similar stormwater control measures?** The GIS team has found that LiDAR imagery alone is not enough to properly separate DDBs from other SCM types with an acceptable level of accuracy. In Greenville particularly, there may not be enough non-DDB SCMs to even form a proper sample for a random forest training dataset. We speculate that the inclusion of additional input layers that can capture and characterize vegetation coverage and surface change after heavy precipitation may increase the accuracy with which the GIS application can predict DDBs against similar features like bioretention cells or stormwater wetlands.

In lieu of additional layers, however, we find it crucial that field validation be incorporated into the recon process. Most of Greenville's DDBs show great variance in dimension and layout, and many of the City's non-DDB features (like roadside ditches and wet ponds) exhibit spatial characteristics that are extremely difficult to differentiate from DDBs when relying only on remote sensing. Field validation is the key aspect of this approach that allows for positive identification of DDBs and other SCM types; without field validations, the GIS model cannot be effectively iterated. Physically going into the real environment to manually inspect each potential site is absolutely necessary to this process.

5.6.3. **Summary.** Overall, the GIS application discussed in this report is still a work in progress, though it has proven to be very capable of identifying SCMs throughout the Greenville ETJ. The GIS team has identified how using LiDAR DEMs and ensemble machine learning can identify engineered depressions in an urban area, and the team is working on improving its capability of differentiating between DDBs and SCMs of other types. As shown in the literature, generating spatial profiles of nested depression stacks is a very good way to differentiate between natural and man-made depressions. However, as suspected, the particular characteristics that vary between SCMs of differing types requires practical field validation in order to observe spatial similarities between real-world basins. Moreover, the GIS team has found that LiDAR alone may not be enough to accurately predict these differences, and additional layers of input data may be necessary. In the time since the initial 25 DDBs were proposed, the GIS application has undergone another iteration of spatial profiling, and a new selection of model predictions will be field verified in the near future. As development continues, the team will include newer DEM data, additional input data types, and expanded spatial profiling characteristics.

At time of writing, the GIS compartment has achieved its minimum objectives; the GIS application has successfully provided a list of confirmed DDBs for further retrofit evaluation. Field surveys will be guided by the CWP team in May 2023, and the retrofit prioritization matrix is under current development. The Greenville DDB Project is currently on target to meet all its objectives within the predicted timeframe. By the end of 2024, the Greenville DDB Project will be ready to propose a list of optimal DDB retrofit candidates to the City of Greenville, which will be implemented to improve the filtration effectiveness and flood risk reduction of the city’s stormwater management network.

6. Internship Reflection: Why Geography?

Geography is a question of "where." Where does stormwater runoff pool in Greenville? Where do the greatest concentrations of debris and pollutants enter the city's water? Where are the areas most affected by local flooding, and where are the people who will be most adversely affected by it? Where are the DDBs?

Geography is as much philosophy as it is science, and properly framing a geographic question is vital to finding appropriate answers. For specific answers to common problems, specificity must be provided in the question. While most people who live in Greenville are aware that some sections of town are prone to flooding, many of the residents don't know exactly where those sections are. While the City's maintenance workers may know that some sections of the stormwater network tend to back up during severe storm events, they may not be able to pinpoint where those backups are happening. Greenville's Stormwater Management department may know that its stormwater infrastructure needs to be updated, but they haven't yet had the ability to answer where those updates need to be implemented first. This internship has been as much an effort to provide specific geographic answers as it has been to pose specific geographic questions.

6.1. Where are Greenville's best DDB retrofit candidates?

While the Greenville DDB Project is still ongoing and the final answers to this question are still forthcoming, my time on this project has been able to provide a preliminary response. Through field validations, the project team has found that there are certain wide, low DDBs throughout the city that have been neglected long enough to have started transforming into natural stormwater wetlands. Stormwater wetlands are among the best SCMs for filtration capacity, and are generally easier to implement than other DDB retrofits. There is still socioeconomic analysis to be incorporated into specific site selection, but these kinds of DDBs that have already turned into ad-hoc wetlands are very good candidates for retrofit. Geography helps us understand the general spatial trends that tend to correlate with these features, which are usually found in large, low-traffic areas, and often are fenced off from pedestrian interference.

6.2. Where are similar problems occurring?

Flooding problems are certainly not unique to Greenville. The Tar River exists as a single stream in a much larger water network that spans the breadth of North Carolina. Before reaching Greenville, the Tar springs from its headlands near Mayo Lake and winds eastward through multiple towns including Louisburg, Rocky Mount, and Tarboro. As the river becomes polluted or clogged, all the communities along its banks will suffer the effects. The Tar isn't the only river that affects Greenville's water, either. The Neuse River Basin borders the Tar-Pamlico Basin to the south, and Greenville has to consider both watersheds as it develops. The Neuse River flows through the Raleigh-Durham triangle to the west, which is a rapidly growing metropolitan center with sprawling developments and impermeable cover. When heavy rains fall over this area, much of the runoff rushes down the Neuse River and strains the capacities of the communities downstream, including the capacity of the natural environment. When either the Neuse or the Tar sees flooding, it is not unlikely to see flooding in Greenville. Likewise, when Greenville floods due to compound events, it is not unlikely to see flooding in other communities along the river network. Maintaining a geographic mindset helps Greenville's planners, policy-makers, and residents understand the ways that local stormwater management issues affect more than just Greenville.

6.3. Where are there other communities that may benefit from this research?

All along North Carolina's coastal plain, there are dozens of communities that are prone to similar stormwater management issues, and these similarities extend far beyond state lines. Urban areas throughout the entire southeast region of the United States will have to find new and better ways to balance their growth and their safety as global climate change continues. Many cities along the eastern seaboard are relatively old, and likely have stormwater infrastructure networks in similar conditions to Greenville's. Having a proven methodology to identify and prioritize their own SCMs may help alleviate some of the challenges associated with improving their own stormwater capacities. Many US citizens are relocating inland away from the coast as affordable property becomes harder to find, and landlocked cities are facing unprecedented growth. As these municipalities form their own plans for this new burst in development, this research may help them understand how upgrading existing stormwater capacity may be a necessary supplement to their networks. Understanding regional geography and spatial trends helps forward-thinking decision-makers anticipate and plan for the environmental problems their communities will likely face in the future.

6.4. Where has this knowledge come from?

It takes specific local knowledge to be able to address specific local problems. This internship has allowed me the opportunity to see a specific, local problem addressed by a multidisciplinary team with extensive situated knowledge of Greenville's unique geography. Every ECU member of the project team (including myself) has been in Greenville for at least five years, and each has formed their own unique perspective on Greenville's geography. Mike O'Driscoll has two decades of knowledge regarding Greenville's relationship with the Atlantic Coast and its river systems. Guy Iverson has been studying water pollution and SCMs in Greenville since 2006. Rob Howard has been honing his GIS skills in a staggering number of environmental analysis projects over the last decade and more. The entire Greenville DDB Project was proposed because these expert geographers had the specific, situated knowledge to be able to recognize Greenville's need for this analysis. Geography is the spatial commonality that allows and encourages experts from all ranges of disciplines to come together to solve local problems.

6.5. **Where else can this knowledge be shared?**

Much in the same way that local problems need local knowledge, regional problems need regional knowledge. Global problems need global knowledge. The extent of the problem is the necessary extent of the solution. Greenville is unique in its history, location, population, development, economy, and landscape, but it is not unique in its need to adapt to a changing world. Though Tennessee isn't a coastal state, it faces the threat of sudden onset flood conditions and compound flood risks all its own. Knowing how to improve existing stormwater management networks may help prepare its riverine communities for unexpected flash flood conditions. While California's central valley may already have an extensive and well-maintained flood management network, it faces the very real threat of land sinking underneath its communities. Having a way to remotely identify and characterize specific depressions may help to understand the extent of land subsidence throughout the area. We all exist in this changing world, and geography helps us find the places where our local knowledge can be applied to broader issues.

6.6. **Where else is there more to learn?**

Geography is infinite. As long as we contend with physical problems in the real world around us, every question will have some component of "where," and geography will always be a framework that helps provide the answer. This is the philosophy of geography. But philosophy alone is not enough to answer the world's geographic questions (of which there are an equally infinite amount). Geography *must* be engaged as a practice in order for it to have any effective value. Geography is the study of spatial relationships, and relationships must be participated in if they are to be truly understood. A better question than "Why is this problem related to Geography?" might be "How are you engaging in the Geography of this problem?" To that I answer, "I engage in this problem because I am *here.*" My geography coincides with the geography of this problem. I have seen the streets of Greenville flood in September. I have talked to the people who have watched their homes wash away. I have waded in the same water that carries the toxic refuse that flows through the Tar. I am here, and Greenville's problems are here, so I will engage in Greenville's problems. But there are geographic problems that extend far beyond the boundaries of Greenville's extraterritorial jurisdiction, and it will require a respectively wider scope of knowledge to be able to answer them. Many of Greenville's most significant problems are in-fact national or global problems, and I will require a greater understanding of the specific aspects of these wider issues if I ever hope to contribute to their solution.

Fortunately for me, and for anyone who shares an aptitude for spatial problem-solving, geography is everywhere.

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Appendixes

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Appendix 1: List of Common Abbreviations & Acronyms

CWA – Clean Water Act

DDB – Dry detention basin

DEM – Digital elevation model

DGPE – (ECU) Department of Geography, Planning, & Environment

ECU – East Carolina University

EPA – Environmental Protection Agency

ETJ – Extraterritorial jurisdiction

GIS – Geospatial information science/systems

GPS – Global positioning system

GSI – Green stormwater infrastructure

LiDAR – Light detection and ranging

MDC – Minimum design criteria

MS4 – Municipal separate stormwater systems

NCDEQ – North Carolina Department of Environmental Quality

NCDOT – North Carolina Department of Transportation

NIR – Near-infrared

NPDES – National Pollutant Discharge Elimination System

RTK – Real-time kinematics

SAR – Synthetic aperture radar

SCM – Stormwater control measure

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Appendix 3: Greenville DDB Project Timeline

TIMELINE	**Year**	**2022**				**2023**				**2024**			
	Quarter	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Project Phase/Milestone	**Months**	Jan.-Mar.	Apr.-Jun.	Jul.-Sept.	Oct.-Dec.	Jan.-Mar.	Apr.-Jun.	Jul.-Sept.	Oct.-Dec.	Jan.-Mar.	Apr.-Jun.	Jul.-Sept.	Oct.-Dec.
Signed MOU		X											
Project Kickoff Meeting		X											
Greenville GIS Coordination Meeting		X											
Quarterly Reports & Reimburse Requests		X	X	X	X	X	X	X	X	X	X	X	
Development of GIS Framework		X	X										
Pre-existing Data Collection		X	X	X									
GIS Development			X	X									
LiDAR and Remote Sensing Analysis				X	X								
Implement GIS					X	X	X	X	X	X	X	X	X
Student Engagement- GIS/Field Sites					X	X	X	X	X	X	X	X	X
Develop Field Assessment Protocols					X								
Field Assessment of Detention Basins						X	X	X					
Map all Dry Detention Basins						X	X	X					
ID/Monitoring of Dry Detention Basins							X	X	X	X	X	X	
Retrofit Prioritization Approach										X			
Retrofit Assessment										X	X		
Map all Potential Retrofit Sites										X	X		
Community Engagement Workshop											X	X	
Develop Retrofit Factsheet											X		
Data Analysis/Final Report Preparation											X	X	X
Proposal Preparation/Submission											X	X	X
Submit Final Report													X

Appendix 4: GIS Script Sample

This script sample shows the process of creating a view of the model results. Predicted DDB fields are (inner) joined with the primary data table to identify positively identified features; the training dataset is (outer) joined with the prediction set to identify any known features that were left unidentified by the model. All calculated attributes are copied to the view.

```
CREATE OR REPLACE VIEW "eeg-ddb-
greenville".elevation_isolines__rings_ex_forests AS
    SELECT
        (t1).*,
        t2.forest_class
    FROM elevation_isolines__rings_ex t1
    INNER JOIN forest_results t2
        ON t1.ogc_fid = t2.ogc_fid;

DROP VIEW IF EXISTS "eeg-ddb-
greenville".elevation_isolines__rings_ex_forests__obc
CASCADE;
CREATE OR REPLACE VIEW "eeg-ddb-
greenville".elevation_isolines__rings_ex_forests__obc AS
    SELECT DISTINCT ON (t1.cid)
        t1.cid,
        t2.*,
        t3.all_pids[1] AS first_pid,
        t3.all_pids[2] AS second_pid,
        t3.all_pids[3] AS third_pid,
        array_to_string(t3.all_pids, ';') AS all_parcels,
        t4.all_subdivs[1] AS first_subdiv,
        t4.all_subdivs[2] AS second_subdiv,
        t4.all_subdivs[3] AS third_subdiv,
        array_to_string(t4.all_subdivs, ';') AS all_subdivs
    FROM (
            SELECT
                row_number() over () as cid,
                t3.geom AS geom
            FROM (
                    SELECT
                        (st_dump(st_union(geom))).geom AS geom
                    FROM "eeg-ddb-
greenville".elevation_isolines__rings_ex_forests
                    WHERE
                        forest_class = 1 AND
                        ix_etj = TRUE AND
                        ix_building = FALSE AND
                        ix_transport = FALSE
                ) t3
        ) t1
    INNER JOIN "eeg-ddb-
greenville".elevation_isolines__rings_ex_forests t2
        ON st_intersects(t1.geom, t2.geom)
    LEFT JOIN "eeg-ddb-
greenville".elevation_isolines__rings_ex__parcels t3
        ON t2.ogc_fid = t3.ogc_fid
    LEFT JOIN "eeg-ddb-
greenville".elevation_isolines__rings_ex__subdivs t4
        ON t2.ogc_fid = t4.ogc_fid
    WHERE t2.forest_class = 1 AND t2.ix_etj = TRUE
    ORDER BY t1.cid, t2.area DESC;

CREATE OR REPLACE VIEW "eeg-ddb-
greenville".elevation_isolines__rings_ex_forests__obc_cntr AS
    SELECT t1.cid,
        t1.ogc_fid,
        st_pointonsurface(t1.geom) AS geom,
        t1.parents,
        t1.children,
        t1.stack_position,
        t1.stack_depth,
        t1.level,
        t1.is_speck,
        t1.is_closed,
        t1.is_depression,
        t1.height,
        t1.width,
        t1.perimeter,
        t1.area,
        t1.volume,
        t1.ix_etj,
        t1.ix_parcels,
        t1.ix_subdivisions,
        t1.ix_hydro,
        t1.ix_transport,
        t1.ix_building,
        t1.ix_channel,
        t1.ix_pipe_end,
        t1.ix_pond_structure,
        t1.ix_drop_inlet,
        t1.ix_slab_inlet,
        t1.ix_yard_inlet,
        t1.ix_soils,
        t1.ix_soils_hydgrp,
        t1.sm_par,
        t1.sm_sci,
        t1.sm_fractal,
        t1.sm_linearity,
        t1.rm_fcar,
        t1.rm_acar,
        t1.forest_class,
        t1.first_pid,
        t1.second_pid,
        t1.third_pid,
        t1.all_parcels,
        t1.first_subdiv,
        t1.second_subdiv,
        t1.third_subdiv,
        t1.all_subdivs
    FROM "eeg-ddb-
greenville".elevation_isolines__rings_ex_forests__obc t1;

SELECT COUNT(*) FROM "eeg-ddb-
greenville".elevation_isolines__attributes WHERE is_speck =
FALSE;
```

Appendix 5: Public Response Table

Comment	Response
Also mention something about increases in impermeable surfaces	Impermeable surfaces are discussed in §2.2.
In Greenville or everywhere? Source for this?	Section removed.
Is there a citation for all this?	Section removed.
How do you tie this to your methods and findings? Stormwater infrastructure is too broad, you are specifically looking at DDBs. Think about refining this.	Research objective has been refined to focus on GIS methodology.
Need a description on decision trees in the proposal. Emphasize "why GIS" in the proposal – why GIS can be used. In literature review, some can be merged into introduction. In lit review, come to what other people did in similar methodologies/topics.	Previous GIS applications are discussed in §2.4. Random forests and decision trees are discussed in §4.3.3.
W*ell, the seas at least…*	Sentence removed.
Not change – sea level rise. Is this by 2100? If so, say so	Sentence revised. See §2.1.1.
In the southeast?	Section removed.
A more robust literature review section is needed and should include: *1. Stormwater systems in the northeast and eastern United States. There is quite a lot of* *documentation on this in the literature. i.e. The types of stormwater systems and* *associated challenges/issues. This section should at a minimum address the combined* *and separate sewer system and how that impacts storm water management.* *2. Previous efforts to document stormwater management in the United States including* *DDBs. What are the challenges faced, what methods have been used, etc.*	Sewer system types and common problems are discussed in §2.1.3. DDB technical specifications are discussed in §2.3.

3. How do you define a DDB, i.e., what are the parameters, how do you identify it?	
Citation?	Citation added.
This will need to be expanded for the report – what are the regulations?	NC SCM regulations are discussed in §2.2.
"Capitol" is the actual building of government. "Capital" is the city where the government presides in.	"Capitol" changed to "capital".
Give source for Figure 1 below the figure.	Citation added.
Same comment. Give source for Figure 2.	Citation added.
What does this mean? It is vague. Recommend to remove.	Sentence removed.
Isn't this stated above?	Section revised.
Move this sentence to the introduction.	Section revised.
Move to lit review.	Section revised.
Provide source for Figure 3.	Citation added.
Very clearly explain your role within the team – don't take credit for more than what you did.	Internship overview is provided in §1.1. Internship expectations are outlined in §3.4. Specific execution of duty is discussed in §4.3.
Add what you are doing in the field and mention the probable/possible clarification. Be also explicit in the subjectivity of this – try to be more systematic	Field validation is discussed in §4.3.3. Field surveys are discussed in §5.3.2.
20 square miles?	Section revised.
"Principal"	Section removed.

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